CLASSIFYING FAILING STATES

THESIS

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Abstract

The US is heavily involved in the first major war of the 21st Century – The Global War on Terrorism (GWOT). As with any militant group, the foundation of the enemy's force is their people. There are two primary strategies for defeating the terrorists and achieving victory in the GWOT. First, we must root out terrorists where they live, train, plan, and recruit and attack them militarily. Second, we must suffocate them by cutting off the supply of new soldiers willing to choose aggression or even death over their current life. This thesis helps to achieve these objectives by applying Multivariate Analysis techniques to identify the states most likely to provide asylum for terrorists.

Weak and Failed States are attractive to terrorist groups looking for safe haven and recruits. Governments in these states are often unable to prevent illegal activity, and are vulnerable to corruption or takeover. Citizens of failing states often experience poverty, disease, and unemployment, and may see little hope for improvement. Terrorists can meet these disenfranchised people's basic needs and promise brighter futures for families of those willing to fight and perhaps die for the cause.

Current published efforts to identify failing states primarily use Ordinary Least Squares Regression, which requires the analyst to predefine the degree to which a state is likely to fail. This thesis uses a Factor Analysis approach to identify the key indicators of state failure, and Discriminant Analysis to classify states as Stable, Borderline, or Failing based on these indicators. Furthermore, each nation's discriminant function scores are used to determine their degree of instability. The methodology is applied to 200 countries for which open source data was available on 167 variables. Results of the classification are compared with subject matter experts in the field of state failure.

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I would first like to thank my advisor, Dr. Richard Deckro, for his unwavering support and guidance throughout this entire study. His continued effort to apply his craft to major issues of the world is inspiring. If I can take even a fraction of his attitude and passion with me throughout my career, my time will have been well spent.

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Nathan E. Nysether

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1. Introduction

1.1. Background

The objective of this thesis is to assist in preventing unstable nations from collapsing or erupting into violent conflict. This is accomplished by providing a mathematical model to classify states as weak or failing based on currently collected and available data. This has the potential to allow the necessary lead time for the international community to be able to take actions to avert a crisis and develop a stable infrastructure necessary to sustain lasting peace. There are two key premises which underlie the importance of such an effort.

First, when compared to conventional warfare and post-conflict reconstruction, it is less costly in terms of lives, dollars, time, public support, and foreign relations to take actions in failing states prior to their collapse or the outbreak of violent conflict. In addition, enhancing the capacity for nations to sustain themselves is more likely to provide long-term peace in crisis-prone countries. (Carment and Schnabel, 2003: 1-2). As shown in Figure 1.1, the Office of Force Transformation is moving the Department of Defense (DoD) toward a strategy of dissuading and deterring violent conflict, rather than merely participating in it when it becomes inevitable.

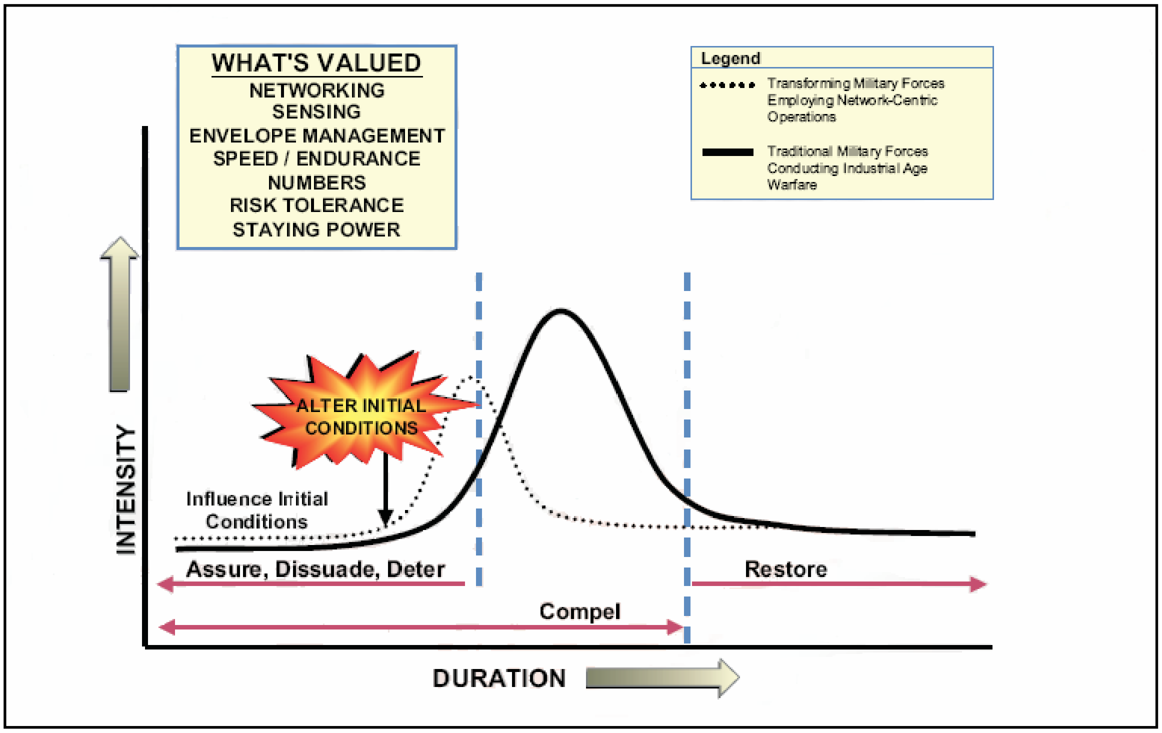

Figure 1-1: DoD Strategy – Deter Forward
(Office of Force Transformation, 2003: 29)

Specifically, DoD Directive 3000.05 dated 28 November 2005 outlines responsibilities within the DoD for Stability, Security, Transition, and Reconstruction (SSTR) Operations. Section 4.2 defines the purpose of these operations:

> "Stability operations are conducted to help establish order that advances US interests and values. The immediate goal often is to provide the local populace with security, restore essential services, and meet humanitarian needs. The long-term goal is to help develop indigenous capacity for securing essential services, a viable market economy, rule of law, democratic institutions, and a robust civil society." (DoDD 3000.05, 2005: 2)

Second, US objectives in the Global War on Terrorism (GWOT) further illustrate the importance of this study. In a White House publication defining our national strategy for combating terrorism, President George W. Bush set as one of the United States' primary goals that of denying terrorists the sanctuary they require to carry out their plans and attacks (Office of the President of the United States, 2003). To do so, the international community must discern which nations are currently, or are in danger of becoming, failed states. Weak states are attractive to terrorist cells looking for asylum and recruits (Forest, 2006: 17-18). Takeyh and Gvosdev describe four key benefits failed states provide to terrorist organizations. First, they provide territory to live, hide and train. Second, failed states often lack legitimate law enforcement capabilities, leaving terrorists free to traffic drugs and amass funds and weapons. Third, as unemployment and poverty are common in failed states, they provide terrorist organizations access to potential recruits looking for a better way of life. Finally, the UN or other foreign countries are less likely to invade sovereign states, even if they are in crisis (Takeyh and Gvosdev, 2002: 98-101).

As resources available for stabilization efforts are always limited, the President calls for a plan to focus allied efforts on those countries most in need of international aid (Office of the President of the United States, 2003: 17). The goal of this thesis then is to assist the US and her allies in allocating their preemptive stabilization efforts by constructing a model to classify states in terms of their stability in order to provide early warning of a potentially failing state.

1.2. Problem Statement

Numerous government and non-government agencies expend considerable resources on collecting data on states throughout the world (See Chapter 2 for a review of various studies). One of the driving forces behind their efforts is a desire to preserve human rights and dignity, and to spread personal and political freedom. Another objective which has taken center stage for most nations is the containment of global terrorism. Should terrorists find a foothold in failing states, it will be more difficult and costly to suppress their threat to freedom in the future. To illustrate this point, consider that the US allocated approximately $87 Billion in 2006 attempting to stabilize Iraq (Congressional Budget Office, 2006: 1), while the House Committee on International Relations estimates only $52 Million will be required to maintain stability and security in The Congo over each of the next two years (S. 2125, 2006:1). Michael Dziedzic summarized the benefits of being proactive rather than reactive in assisting failing states:

> Neglect is not a strategy. It is, rather, a guarantee that the price of intervention will inevitably become exhaustive. The better alternative is to become proficient at transforming internal conflict. (Covey *et al*, 2005: 281)

To successfully preserve human rights and thwart terrorism, appropriate decisions must be made regarding the allocation of precious stabilization and conflict prevention resources leading to greater cost savings in the long run. This thesis contends that such decisions can be aided by a rigorous application of Operations Research (OR) techniques to currently collected and available data.

Several models exist for predicting failing states. Often, however, limited justification is provided to support the choice of model, or the data used in making predictions. In this thesis, multivariate statistics techniques are employed to help crisis analysts select the appropriate data to collect, and to help identify failing states.

1.3. Approach and Methodology

This thesis proposes Factor Analysis (FA) and Discriminant Analysis (DA) approaches to identify the variables most significant in providing early warning of failing states. Regression methods often used in the literature rely on predetermined state crisis scores to serve as dependent variables (Rowlands and Joseph in Carment, 2003; Poe *et al*, 2006), which assumes the analyst can accurately define and determine the level of crisis in a country *a priori*, independent of the variables later used to build the regression model. In contrast, FA regards observable variables as reflective indicators of underlying, unobservable factors (Dillon and Goldstein, 1984). When primary factors emerge, variables reflecting these factors can be identified. DA can be used to build a discriminant function if we have an agreed upon list of currently failing or weak states, without necessitating a quantification of such a listing. Merely identifying states as weak will allow for an exploration into the observable data available for such states and allow us to quantify why it might be failing.

Once the key variables have been identified, DA can further be used to construct an appropriate classification model. DA uses multiple independent variables to divide a set of observations, for example states, into two or more categories such as failing or stable. The key variables determined using the FA and DA techniques will serve as the set of independent variables, and DA will differentiate between countries in such a way as to provide the least variation within groups, based on the information contained in those variables.

1.4. Research Scope

The focus of this thesis is on determining what factors are significant predictors of failing states, and constructing a model or models to classify nations based on these factors. Our first hypothesis is that there are measurable, statistically significant differences between states currently defined as Stable, Borderline, and Failing. Our second hypothesis is that as few as ten variables currently being collected and available through open source can, in general, be used to accurately classify nations as weak or failing. Furthermore, Discriminant Analysis, particularly when coupled with Factor

Analysis, is an effective tool for classifying states based on those ten key variables. Currently existing models are evaluated and discussed. While this study serves to help focus international data collection and stabilization efforts, it does not recommend courses of action for the US in any specific failing nation, nor does it provide methods for garnering Congressional or other support for implementing preemptive measures. Figure 1-2 presents the basic progression of crisis intervention efforts, with the portion addressed by this study highlighted.

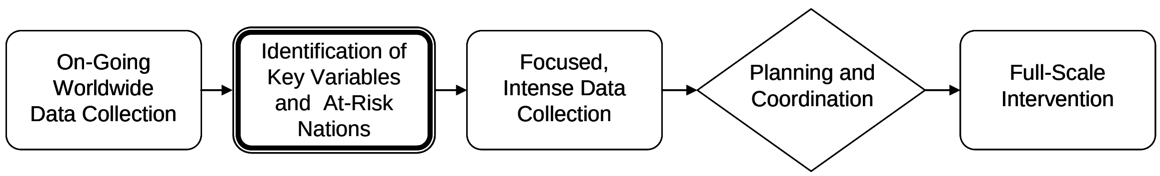

Figure 1-2: Research Scope – Identify Variables and Critical States

If violent conflict were to be thought of as a raging fire, then this thesis purports to describe the chemistry of the fire's fuel. It does not, however, examine the sparks which ignite the fuel. Often, as a state fails and the fuel of instability becomes more and more explosive, it can remain dormant for long periods of time in the absence of a triggering event, or spark. These triggers can come from the government, the people, or from outside forces (Brown, 2001: 15-17). This thesis does not attempt to characterize or predict the single events that ignite conflict, but rather it describes the conditions in which a spark is most likely to result in state failure.

Finally, for the purpose of maximizing usability, the data in this study is limited to open-source. Often, data availability is overused in determining which variables are critical for analysis (Bredel, 2003: 119). It would be an overstatement to conclude that the variables identified in this study are the only data to consider when predicting failing states. However, if certain conditions reflected in the data could indeed be sufficient to declare a nation to be in or approaching crisis, the analysis can be considered adequate if not entirely comprehensive. Furthermore, the methodologies proposed could readily be extended to any data available to the analyst.

1.5. Assumptions

Several key assumptions are necessary for the proposed methodology in this thesis to be relevant. First, data used to construct the model was available in open-source format and the assumption is made that similar data will continue to be collected and made available. The usefulness of the proposed model is reliant on the ability of analysts to effectively acquire the necessary data at limited additional cost. An underlying secondary assumption is that analysts will use this model to assist decision makers in identifying where the US should focus its attention and perhaps perform to a more intensive data collection. Once key states of interest have been identified, a detailed situational analysis may be in order before attempting to justify the additional expense of military, economic or diplomatic assistance or, ultimately, intervention.

Whenever possible, data was collected from a single source. However, when it was necessary to draw from multiple sources, it was assumed that each source used equivalent collection and reporting methods unless otherwise specified. Any violations of this assumption have been noted.

1.6. Overview

Chapter 2 of this thesis provides a review of relevant literature, including a discussion of currently existing models used to assist in the early warning of failing states. For each model, the predictor variables used by that model are identified. A brief overview of various OR techniques is also provided in Chapter 2. More detailed descriptions of Factor Analysis and Discriminant Analysis, and how each was applied to construct the early warning model, are outlined in Chapter 3. In Chapter 4, several models are provided and applied to each of the 200 countries in the dataset. The results are compared and contrasted with the work of subject matter experts in the field of state failure. Chapter 5 concludes this study with a discussion of the relevance of this thesis, significant insights gained and recommendations for future research.

2. Literature Review

2.1. Introduction

This chapter begins with a review of the pertinent literature dealing with conflict prevention through the use of predictive modeling of failing states. Included is a discussion of the merits of taking preemptive action to include relevant guidance from US foreign policy.

Various authors and organizations have used mathematical modeling to attempt to predict failing states; the most common approach has been Ordinary Least Squares Regression (OLS). Therefore, a review of OLS and its underlying assumptions is provided next, as well as current applications to conflict prevention. Other, less common, techniques are also discussed.

Following a review of current approaches to conflict prevention, the Operations Research techniques proposed in this thesis are introduced. A case is made for employing Factor Analysis and Discriminant Analysis to predict failing states, and both techniques are explained.

2.2. Crisis Prevention

One can intuit that violence, death, poverty, disease, extreme violations of human rights and other such occurrences are less desirable than peace, health, personal freedom, security, and life. It is also clear that people in various regions of the world experience varying levels of each of the aforementioned conditions at different times. What is not so obvious is what causes a nation to reach "Crisis" or "Failing" level and, for that matter, exactly what constitutes a nation in crisis. It is these questions that this thesis and the literature reviewed here attempt to address.

2.2.1. Terms and Definitions

Throughout the literature, social economists and political scientists often use several terms and phrases interchangeably to describe key concepts. What may be considered conflict or crisis under one definition may not under another. This section defines some of the key terms as they are used in this thesis.

Accelerator or Trigger. A significant event or change in a key factor which could cause an unstable state to fail or fall into crisis (Schmid, 1998:7). Triggers can be absorbed in most cases by stable states with little or no catastrophic effects. Examples include the 2000 US Presidential election or illegal immigration from Mexico into the US, which have not, to date, led to national crisis by any of the accepted definitions. Jordan's expulsion of Palestinians in 1970 however, may be considered a trigger for the Lebanese Civil War of 1975 (Brown, 2001: 16).

Aggression. Aggression is simply the application of armed force (Schmid, 1998:8). This refers to force applied by national military forces, non-state groups within a nation, or transnational groups when applied to other nations, groups, or civilian population. The term aggression is usually not used to describe force applied by third-party peacemaking organizations, such as the UN.

Armed Conflict. When aggression is applied between two groups, both of which possess weapons of war, it is called Armed Conflict (Schmid, 1998:8).

CNN-Factor. The CNN-Factor refers to the emotional reaction of the public to media coverage of events or conditions. Debate continues as to how a public's reaction to what they see on TV can influence their government's response to a crisis in another country (Schmid, 1998:11). A second CNN-Factor concerns people within a country involved in conflict. Among others, Barnett (2005) and Brown (2001) claim that as people in globally disconnected countries become aware of their own conditions as compared to the rest of the country, region or world, conflict may arise from their perception of imbalance in standard-of-living.

Conflict Prevention. Proactive strategy to identify necessary conditions for stability, and take actions to create those conditions (Carment and Schnabel in Carment, 2003: 11). Note that by this definition, *conflict* is more synonymous with instability, not necessarily violence; with the conditions which may lead to violence, not the resulting violence per se.

Failing or Failed State. One of the primary objectives of this thesis is to refine the definition of a *Failing* or *Weak State* by identifying the key variables used to measure national stability. In broad terms, governments exist to provide the people within a defined region a wide spectrum of public or political goods (Forest, 2006:18-19). Use of the terms Failing, Weak, or Collapsed States earlier in this thesis refers to a state in the unquantifiable condition of being unable to successfully provide these services to its citizens. Such states may require outside intervention to avoid violent conflict and significant terrorist infiltration.

Genocide. Genocide includes any attempt to destroy a group of people for religious, ethnic, national, or racial reasons (Schmid, 1998:15). Actions may include, but are not limited to, armed conflict, mass murder, prevention of birth, or child abduction.

Peace. Peace is typically defined as the absence of conflict, instability, repression, and poverty or the process of working to achieve such a condition (Schmid, 1998:19).

Peacekeeping. Peacekeeping refers to efforts taken usually in the presence of latent, increasing conflict to prevent the conflict from escalating into violence (Bredel, 2003: 9-11). Peacekeeping often involves direct third-party involvement in resolving only the conflict itself, rather than considering the underlying conditions necessary for long-term peace. Peacekeeping ends when the immediate threat of violence has waned.

Peacemaking. Peacemaking refers to efforts taken during conflict to restore peace (Bredel, 2003: 9-11). This is the portion of the peace process most commonly associated with third-party military intervention. However, this pattern is not ideal as explained by UN Secretary Kofi Annan in his 1998 address in response to the Carnegie Commission final report on preventing deadly conflict:

> "…we seem never to learn. Time and again differences are allowed to develop into disputes and disputes allowed to develop into deadly conflicts. Time and again, warning signs are ignored and pleas for help overlooked. Only after the deaths and the destruction do we intervene at a far higher human and material cost and with far fewer lives to save. Only when it is too late do we value prevention." (SG/SM/6454, 1998)

This sentiment underscores the importance of identifying and providing early warning of failing states.

Peace-building. Peace-building refers to efforts taken in the absence of conflict, either before or after, to prevent future conflict (Bredel, 2003: 9-11). It is in this stage where this thesis proposes to provide the most benefit, with the goal of assisting in identifying which states, and which factors, require the most attention to achieve long-term peace.

Stability Operations. This is an umbrella term encompassing all military and civilian activities conducted to establish or maintain order (DoDD 3000.05, 2005: 2).

2.2.2. Recent and Ongoing Crisis Prevention Efforts

Crisis prevention is a key objective for the US as well as the global community. DoD directive 3000.05 states that stability operations are critical to US interests and values. One of our most urgent interests is to prevent the spread of terrorism and to root out terrorist organizations where they live, work and train. Failed states, or nations in crisis, provide ideal conditions for terrorists to carry out their missions (Takeyh and Gvosdev, 2002: 98-101, Forest, 2006:17-18). To that end, the DoD has outlined roles and responsibilities for crisis prevention across the entire spectrum of agencies to include foreign and international governments, as well as non-government (NGO) and private organizations (DoDD 3000.05, 2005: 3).

Dr. Thomas P.M. Barnett, who has been working in national security affairs for a number of years, has received significant attention for his work in identifying and predicting the nations most likely to cause concern for the United States, to include failing or failed states. He has published several books and a number of articles on the subject and has given over 1,000 briefings to leaders and decision makers both in and out of the DoD and throughout the world (Barnett in *Esquire*, 2003). His books, *The Pentagon's New Map* (2004) and its follow-up text *Blueprint for Action* (2005), provide a breakdown of states which are most critical from a US strategic standpoint. Barnett claims that countries which are left out of the global economy, or "Gap Countries", are most in danger of collapsing, and thereby providing safe haven for terrorist groups. The basis for the conclusion that these Gap countries are most likely to be areas of concern for the US echoes the 9/11 Commission Report:

> Economic openness is essential. Terrorism is not caused by poverty. Indeed, many terrorists come from relatively well-off families. Yet when people lose hope, when societies break down, when countries fragment, the breeding grounds for terrorism are created. Backward economic policies and repressive political regimes slip into societies that are without hope, where ambition and passions have no constructive outlet. (9/11 Commission Report, 2004: 395)

The popularity of Barnett's work, and its parallels with the 9/11 Commission, underscore the importance of this study. This thesis complements these efforts by providing the added benefit of objective, reproducible measures of states' likelihood of failure. Barnett's classification serves as one of the bases for the Discriminant Analysis used in this thesis; a comparison between his classification and the DA results can be found in Chapter 4.

On the global scale, in 2000 the United Nations adopted a resolution agreeing to work toward eight common goals directed at reducing poverty, disease and violence; increasing education, women's rights and tolerance; and protecting human rights, peace, and the environment (UN Resolution 55/2, 2000). This resolution led to the development of the Millennium Development Goals (MDG) Indicators; a list of 48 measures used to gauge the world's progress toward achieving the MDG. The UN Common Database, which contains the MDG data, can be found at http://unstats.un.org/unsd/default.htm. The MDG indicators are listed in Appendix A. Here too there is great value added, specifically by the collection of observable data on all countries. This thesis builds on the UN data collection efforts by identifying which variables are statistically most important, and using those variables to make predictions as to where the next crisis may arise.

There are a number of studies in the literature attempting to predict failing states and prevent conflict. The published work in this area has been primarily done by economists and political scientists. Some, such as Barnett, apply "soft science" techniques based on the idea that while it may be difficult to define or quantify crisis, we know it when we see it. Others have employed statistical techniques, most commonly Ordinary Least Squares Linear Regression. The following sections provide an overview of regression analysis and how it has been used, a brief commentary on other statistical techniques found in the literature, and an introduction to the methods used in this study.

2.3. Commonly Used Operations Research Techniques and Applications

2.3.1. OLS Regression

Ordinary Least Squares (OLS) Linear regression is currently the most common method used in the literature for the prediction of failing states. This appears to be so for several reasons. First, if an analyst desires to predict or estimate the future level of a response or dependent variable using available data, e.g. predicting future crisis levels based on current inflation rates, OLS may be the appropriate tool (Montgomery, Peck, and Vining, 2001: 11). In addition, when used appropriately, regression can provide a logical, intuitive model which illustrates the relationship between the variable of interest and each of the predictor variables used in the model. Finally, due to its frequent use, regression is widely understood, especially within the economic and political science fields (Wonnacott and Wonnacott, 1979).

However, there are potential drawbacks to using OLS regression to predict failing states. There may be difficulty defining a response variable, violations of the fundamental assumptions of regression - in particular severe multicollinearity of regressors, and the possibility of overstating or misinterpreting results. The following sections examine these issues in turn, and provide rationale for using the alternative methods employed in this study.

2.3.1.1. Response Variables

OLS Regression analysis is used to model the relationship between one or more independent variables, also called predictors or regressors, and a single dependent variable, also known as the response variable. For example, a person may be interested in predicting the amount of time it will take him to get to work. He might hypothesize that a regression model should include such regressors as distance, traffic levels, and weather. Knowing the levels of these three variables may provide a decent prediction as to the amount of time needed to drive to work. This simple example highlights an important concept. The cornerstone of any regression analysis is the variable of interest – the response variable. In this example, the average time required to get to work is the response, and it is conveniently objective, measurable, and quantifiable. However, if the variance of the time to get to work were large or skewed toward the right, one might be late too often to keep ones job, even if the average time needed model was significant. When attempting to predict failing states, we may not even have the ability to identify a response variable.

There are as many response variables used for predicting crises as there are studies done on the subject. Rowlands and Joseph in Carment's book *Conflict Prevention*, 2003 rated countries with an integer from 0 to 3 on a conflict intensity scale. A rating of zero was given to countries that experienced little or no violence in a given year, while a rating of three went to countries involved in major conflicts such as civil war (Carment, 2003: 226-7). Of course, the aim of Rowlands and Joseph's study was only to predict conflict, not failing states. However, it is a contention of this study that the two phenomena are intertwined. For the purpose of predicting unstable and failing states, level of conflict could certainly be considered important, but there is a question of whether it should be a predictor or a response variable, and if it is the only variable that should be considered analogous with crisis.

Nafziger and Auvinen in a 1997 paper went a step further and proposed a single dependent variable which was the result of a direct calculation involving four other variables: number of people killed in battles, infant mortality rate, daily calorie supply per capita, and number of refugees and displaced persons (Nafziger and Auvinen, 1997: 14-17). They used these proxies because they had predefined their variable of interest as a Complex Humanitarian Emergency (CHE) score, where a CHE was further defined as having large numbers of people dying or suffering from war, disease, hunger or displacement (Nafziger *et al*: 1). Again we see that defining the dependent variable lays the foundation for the regression analysis, but as before we are left with questions as to how these variables were chosen and assigned to be predictors or responses.

Poe, Rost and Carey in 2006 use a Political Terror Scale (PTS) derived by Professor Mark Gibney of the University of North Carolina as an indication of crisis manifested in the occurrences of human rights violations (Poe *et al*, 2006, 490-1). Dr. Gibney compiled data from various sources, primarily the US State Department and Amnesty International. He and his team assigned an integer score of 1 to 5 based on the following criteria:

> Level 1: Countries under a secure rule of law, people are not imprisoned for their view, and torture is rare or exceptional. Political murders are extremely rare.
>
> Level 2: There is a limited amount of imprisonment for nonviolent political activity. However, few persons are affected, torture and beatings are exceptional. Political murder is rare.
>
> Level 3: There is extensive political imprisonment, or a recent history of such imprisonment. Execution or other political murders and brutality may be common. Unlimited detention, with or without a trial, for political views is accepted.
>
> Level 4: The practices of level 3 are expanded to larger numbers. Murders, disappearances, and torture are a common part of life. In spite of its generality, on this level terror affects those who interest themselves in politics or ideas.
>
> Level 5: The terrors of level 4 have been expanded to the whole population. The leaders of these societies place no limits on the means or thoroughness with which they pursue personal or ideological goals.
> (http://www.unca.edu/politicalscience/images/Colloquium/faculty-staff/gibney.html, 18 October 2006)

In our DA, we found Dr. Gibney's Political Terror scale to be valuable for discriminating failing states.

Each of the aforementioned studies attempts to explain or predict various crises by concentrating on some observable variable(s). But we would still need to determine what truly defines a national crisis or humanitarian emergency or failing state in order to use OLS. In contrast, rather than identifying a single variable as our crisis level indicator, this thesis proposes exploratory Factor Analysis to determine a set of key variables most useful in characterizing the overall status of nations. Discriminant Analysis can then be used to analyze the classification of states on the basis of these variables. This non-reliance on defining and calculating a dependent variable allows us to explore all available data, and identify weak or failing states based on their similarities to countries whose overall status is known.

2.3.1.2. Assumptions

A second pitfall in using OLS Regression analysis for predicting failing states deals with the assumptions analysts must make in order for regression analysis to provide reasonably valid results. First, the relationships between the predictors and response variable are assumed to be at least approximately linear. Second, the error terms, which are the differences between each of the observed values of the response variable and the values predicted by the regression model, are assumed to be normally distributed with a mean of zero and constant variance. Third, the error terms are assumed independent and uncorrelated (Montgomery *et al*, 2001: 131).

The first assumption necessary for ordinary least squares regression (OLS) to be appropriate is that there is at least an approximately linear relationship between the independent "x" variables and the dependent "y". Often a simple scatter plot of the data will confirm or refute the claim of a linear relationship. The scatter plots shown in Figure 2-1 demonstrate the dangers of violating the linearity assumption.

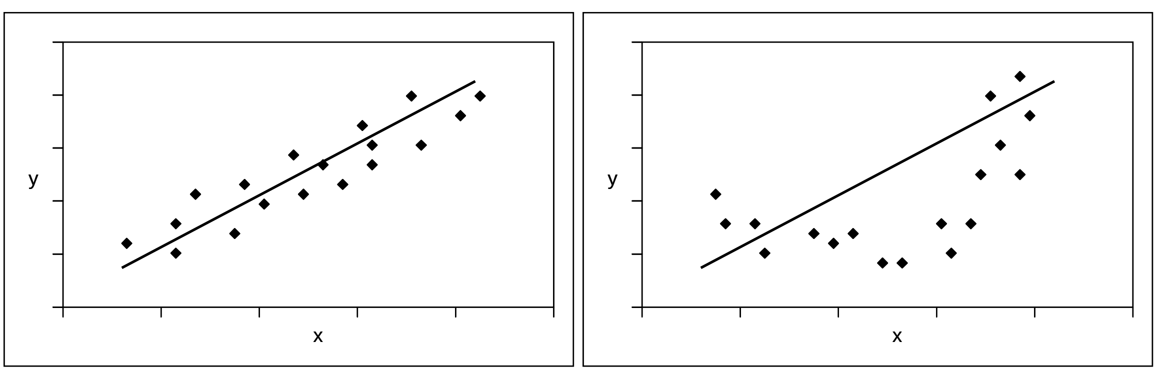

Figure 2-1: Situations in which OLS a) is and b) is not appropriate
(Montgomery *et al*, 2001: 27)

In both cases, an identical OLS model may be statistically significant. However, a strictly linear model will probably not sufficiently explain the relationship between x and y in Figure 2-1 b. As an example from the failing states literature, Brown claims that the more repression minorities experience in a nation, the more likely it is that the nation will erupt into war and crisis (Brown, 2001: 29). However, Ian Bremer describes a different phenomenon in his 2006 book "The J-Curve". He contends that nations can be effectively stable with a repressive government such as in North Korea, or a free and open government such as the US, and that the truly unstable countries are those in between. As nations move from a "stable, closed" state in which minority repression is high to a "stable, open" state, they will traverse a very unstable period (Bremer, 2006). In other words, repression and national stability may be related in a fashion similar to what is shown in Figure 2-1b and not in a truly linear fashion.

Similarly, freedom of the press is often considered a sign of a more stable government, and therefore a more stable nation. However, Snyder and Ballentine in Brown, 2001 claim that without a stable government already in place, a free press may actually cause more harm than good, at least in the short term (Snyder and Ballentine in Brown, 2001). The media can raise people's awareness of the inequalities to which they had previously been oblivious, inciting aggressive action in some cases. This phenomenon is sometimes known as the CNN factor. An example is television coverage depicting a higher standard of living in a neighboring nation than is experienced at home.

To address the issue of non-linear relationships between independent and dependent variables, it is often desirable to transform one or more of the variables (Montgomery *et al*, 2001: 27). For instance, introducing a squared term in the situation in Figure 2-1 b may yield a linear relationship. Applications of such transformations are demonstrated in the methodology portion of this thesis.

The second assumption in OLS is that the residuals, or error terms, are normally distributed with a mean of zero and constant variance. When the variance of the error terms is constant it is called homoscedasticity. If the variance changes for different levels of *x*, it is called heteroscedasticity. The danger posed by heteroscedasticity is that the OLS model may appear more significant than it truly is; which is to say the confidence level of inferences made using the model may be artificially high (Lattin *et al*, 2003, 58). Consider the scatter plot in Figure 2-2 which shows severely heteroscedastic data. The OLS regression line may be a good predictor of y for lower levels of *x*, but as *x* increases, the model's accuracy decreases. This trend may not be apparent if residuals are not checked.

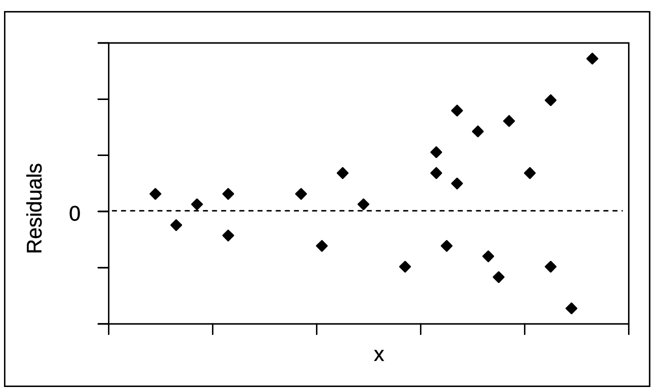

Figure 2-2: Heteroscedasticity
(Lattin *et al*, 2003: 58)

Heteroscedasticity is most often, but not exclusively, encountered when considering changes in variable levels over time (Wonnacott, 1979: 194). For example, as a state becomes involved in conflict of increasing intensity or seems to be inching towards conflict, not only the number but the variation in the number of battle related deaths may increase. Transformations of variables may reduce heteroscedasticity, or an analyst may employ Weighted Least Squares which assigns lower weights to observations with higher variances. This has the effect of creating a model whose parameters are based to a greater extent on data for which the predictions are believed to be more accurate.

The third underlying assumption in OLS is that the error terms are independent and uncorrelated. Ideally, the errors will be random and knowing the error at one level of the independent variable will say nothing about the expected error at the next level. If a pattern exists in the error terms however, for example several positive error values, followed by several negative values, and so on, autocorrelation may be present. This can also be the case if each positive error tends to be followed by a negative error and vice-versa. As with heteroscedasticity, autocorrelation can lead to overstating the confidence of our model (Lattin *et al*, 2003: 61). Again, transformations or a Weighted Least Squares approach may be necessary.

2.3.1.3. Multicollinearity

Multicollinearity occurs when one or more of the independent variables are correlated. It can also occur if one of the variables is close to a linear combination of one or more of the others. With behavioral or economic data, multicollinearity is always present; it is a question of degree. An example of where an analyst might encounter multicollinearity would be building a model using average caloric intake per person, and percentage of the population suffering from malnourishment. While one measures calories, and the other measures a percentage, both variables are closely inter-related.

When multicollinearity is present, the variances and covariances can become quite large and hence the confidence level we have in our model decreases; or conversely, the confidence interval around our model grows larger. If we remove variables which are collinear with other variables left in the model, the model parameters remain unchanged, but the confidence intervals become tighter (Wonnacott, 1979: 354). This has the added benefit of reducing the number of variables required to make predictions.

Removing variables from our model, however, does have the drawback of losing whatever additional information those variables contain, minimal though it may be. In Factor Analysis, it is not necessary to remove variables from the model purely on the basis of multicollinearity. Instead, we may reduce the dimensionality of the data into its primary factors while retaining all available information.

2.3.1.4. Interpretation of Results

It can often be difficult to interpret the results of any analysis and recommend courses of action based on those results. OLS Regression is no exception. Once the appropriate variables are selected and the best possible model is created from these variables, analysts are still left to attempt to explain what the model tells us, and of course what it does not.

First, we must be careful not to assign causal relationships to variables in the OLS model. Even if a correlation has been identified, it is not necessarily true that changing the value of one variable in the real world will directly affect the other (Montgomery *et al*, 2001: 42). Rowlands and Joseph in Carment, 2003 provide an excellent example of such a dilemma. In their effort to explore the causes of internal conflict, they found that if the average inflation rate of a country increases, so does that country's level of internal conflict. Conversely, as involvement of the International Monetary Fund (IMF) increases, internal conflict tends to decline (Rowlands and Joseph in Carment, 2003: 217). The authors caution against claiming that reducing inflation would necessarily cause a reduction in the level of internal conflict, and remind the reader that the IMF has anti-inflationary policies as a condition of their financial support (Rowlands and Joseph in Carment, 2003: 217). In other words, the reality of the situation may be that IMF involvement actually causes both inflation and civil conflict to decrease, and that simply reducing inflation will not by itself lead to decreasing conflict. It may also be true that none of the aforementioned variables are causally related to each other at all. A third possibility, and the one explored further in this study, is that they are merely reflections of some underlying factor not fully accounted for in the model.

A second issue that arises, even with a perfectly constructed model, is determining and reporting how well the model actually describes the data. Essentially, we need a measure of how accurate we believe the model to be as a predictor of the dependent variable. A reader must be careful not to draw conclusions or take radical action based on predictions from a poorly fit model. Often, in the failing state literature, the exclusive measure of how well the model fits the data is the coefficient of determination, also called R-square.

Simply stated, the R-square value of an OLS Regression model is the proportion of variation in the dependent variable which can be explained by the independent variables included in the model (Montgomery *et al*, 2001: 39-40). It is the ratio of the amount of variation explained by the regressors to the total amount of variation in the dependent variable (Montgomery *et al*, 2001: 39).

$$R^2 = \frac{SS_R}{SS_T} = \frac{\text{Regression Sum of Squares}}{\text{Total Sum of Squares}} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2}$$

Where

y_i = observed value of the ith response
$\hat{y}_i$ = predicted value of the ith response
$\bar{y}$ = mean of responses

R-square values range from 0 to 1, with values close to 1 indicating that most of the variation in *y* can be explained by *x*. This does not guarantee that the model sufficiently explains the relationship between *y* and *x* however. Referring back to Section 2.3.1.2, the R-square values for the OLS model in Figure 2-1 may be equal and close to 1, but the model is clearly more representative of the data shown in Figure 2-1a (Montgomery *et al*, 2001: 40).

While a large R-square value does not guarantee that our model is sufficient, a low R-square does suggest that our model is inadequate, or at least does not explain a substantial amount of the variation in our item of interest. There is no universally recognized minimum acceptable value for R-square, but low values indicate the potential for more comprehensive measures to provide useful insights. During this literature review, we encountered no R-square values greater than .20, suggesting there is significant room for improving our abilities to predict failing states.

2.3.2. Other Techniques from the Literature

Regression analysis is by far the most commonly used technique for predicting failing states found in the literature. However, several other methods have been employed. The Fund for Peace uses a Conflict Assessment System Tool (CAST) to scan published articles from around the world for key words like “repression”, “war”, and “famine”. CAST highlights articles based on the frequency of these indicator words or phrases, and those articles are reviewed by subject matter experts (Baker, 2005: slide 9). The experts assign a final score for each country in each of twelve categories: Mounting Demographic Pressures, Massive Movement of Refugees and IDPs, Legacy of Vengeance - Seeking Group Grievance, Chronic and Sustained Human Flight, Uneven Economic Development along Group Lines, Sharp and/or Severe Economic Decline, Criminalization or Delegitimization of the State, Progressive Deterioration of Public Services, Widespread Violation of Human Rights, Security Apparatus as "State within a State", Rise of Factionalized Elites, and Intervention of Other States or External Actors (http://www.fundforpeace.org/programs/fsi/fsindex2006.php, 2006). The scores are summed and the nations are ranked in order of likelihood of failure. The Fund for Peace’s 2006 State Failure Index serves as a second *a priori* classification for this thesis.

Recall that when the data being used do not appear to be linearly related to the response variable, variable transformations may be used. For example, Nafziger and Auvinen, 1997 found that taking the natural logarithm of all independent variables resulted in a stronger linear relationship with their Complex Humanitarian Emergency

(CHE) score (Nafziger and Auvinen, 1997: 14-17). Deciding which variables to transform, and which transformation to use, is no simple task. Throughout this literature review, we found only logarithmic transformations to have been used to date.

2.4. Analysis Techniques Considered for This Thesis

This section provides a brief overview of each of the techniques used in this thesis. It begins with a discussion of various methods for dealing with missing data. This is followed by an introduction to Factor Analysis and Discriminant Analysis.

2.4.1. Missing Data

Invariably, once a researcher leaves the confines of a controlled environment and begins collecting "real-world" data, he will be confronted with the problem of missing or incomplete data (Allison, 2001: 1). For this study, 165 variables were collected on 242 countries covering the period 1995-2005. However, not surprisingly, almost half of the data were missing. This section discusses some of the common terminology and techniques used to address the issue of missing data. For comparison's sake, common techniques found in the scholarly literature are reviewed, though not all were utilized in this study. Details on the implementation of the specific methods used in this thesis can be found in Chapter 3.

2.4.1.1. Terms and Definitions

Missing Completely at Random (MCAR). Data are said to be missing completely at random if the probability of encountering missing data for a particular variable is not dependent on the value of that variable, or any other in the dataset (Allison, 2001: 3). This would be the case if, for example, the probability of being able to find the GNP of a country was in no way related to that country's GNP or any other factor. If the probability of finding a country's GNP increased as the value of GNP increased, the data would not be MCAR. When data are MCAR, the observed data can be regarded as a random sample of the original dataset (Allison, 2001: 3).

Missing at Random (MAR). Data are said to be missing at random if the probability of data missing on one variable is independent of the value of that variable, once all other variables have been considered (Allison, 2001: 4). This would be the case if GNP was more likely to be missing for smaller countries, but within the groups of smaller and larger countries, the probability of GNP missing did not depend on the value of GNP itself.

Missing Data Mechanism (MDM). The missing data mechanism is the set of parameters that describe the probability structure of missing data (Allison, 2001: 5).

Ignorable MDM. In some cases the missing data mechanism can be ignored when performing analysis. This is true if the data are MCAR, or MAR and the MDM is unrelated to the parameters of interest (Allison, 2001: 5). Most often, MAR implies Ignorable MDM (Allison, 2001: 5).

Non-ignorable MDM. If the data are not MAR, the MDM should be included when estimating the parameters of interest as it contains some information about the true structure of the data (Allison, 2001: 5). For example, since it may be valid to assume that failing or failed states are more likely to experience missing data, a variable called "Data Availability" was added to our dataset. This variable was equal to the percentage of data filled in for each country on all other variables. This variable could capture at least a portion of the MDM.

2.4.1.2. Common Missing Data Techniques

List-wise Deletion. List-wise deletion involves removing any observations from the dataset which have any missing values (Allison, 2001: 6). This has the advantages of being easy to implement and leaving the analyst with a dataset containing no missing values, but potentially discards valuable information contained in the incomplete records. For this study, no country was populated for every variable for every year. Therefore, list-wise deletion would result in an empty dataset.

Pair-wise Deletion. Pair-wise deletion is less wasteful than list-wise deletion in that it takes each variable in the dataset two at a time and calculates the means, standard deviations, and covariances or correlations using all of the data available for both variables (Allison, 2001: 6). Therefore, while list-wise deletion would entirely leave out a record with any missing data, pair-wise deletion would only exclude each record from calculations involving the variable(s) for which that record was lacking data. However, pair-wise deletion produces biased standard errors and test statistics, and performs worse than list-wise deletion when correlation among variables is high (Allison, 2001: 9).

Imputation. Imputation describes any method for replacing missing values with some logical estimate of their true value (Allison, 2001: 12). Three more common imputation methods are Mean Substitution, Hot-Deck Imputation, and Multiple Regression (Chantala and Suchindran: 2006: 9), which are described next. It should be noted that if imputed datasets are analyzed with no account for the uncertainty in the imputed values, results will appear as though all data used was authentic. This means the quality of the standard errors and test statistics will be artificially inflated (Chantala and Suchindran: 2006: 9).

Mean Substitution. Mean substitution is done by simply imputing missing values with the mean of the available values for each variable (StatSoft, 2006: n.pag.). This method leads to artificially low estimates of variance and standard errors and should be avoided if at all possible (Allison, 2001: 11).

Multiple Regression Imputation. Multiple regression imputation uses those variables for which we have data and regresses the missing variable on them to generate a predicted value for the missing data (Allison, 2001: 11). For example, if we have three variables X, Y, and Z, with 30% of the data missing for variable Z, we can regress Z on X and Y for the complete cases, and use the resulting equation to generate predicted values for Z in the incomplete cases. The assumption here is that the populated variables are good predictors of the incomplete ones. This method becomes quite complicated when, as in our case, data is missing on more than one variable (Allison, 2001: 11-12).

Maximum Likelihood. Essentially, the method of maximum likelihood estimates population parameter values by selecting those which would maximize the likelihood of the observed data (Wackerly, 2002: 449). Using the maximum likelihood parameters, missing values are imputed by randomly drawing from the estimated population distribution. This technique relies heavily on the assumption that data are MCAR, as imputed values for a given variable will be drawn in the same manner for each observation, independent of any of the other variables in the dataset.

Hot-Deck Imputation. Hot Deck Imputation refers to any technique in which the missing values are replaced by actual observed values for some other record in the dataset, as opposed to means or random draws from a distribution. One benefit of such a technique is that we are guaranteed to replace the missing data with a feasible value, as it had to be observed originally to be a candidate. This prohibits draws from outside the true range of the variable and preserves non-negativity constraints. Furthermore, the nature of the variable such as categorical or binary is preserved. This is similar to Mean Substitution, but rather than using the mean of the entire sample, different values may be used to replace each missing value. While the variation in such a dataset will still be artificially low, it will be greater than that of using the mean for every imputation. There are multiple ways to determine which value to substitute in each case. One such method is discussed next.

Nearest Neighbor Hot-Deck Imputation. Nearest Neighbor Imputation (NNI) is an intuitive and easily implemented approach to addressing the issue of missing data, and is the technique employed in this thesis. As its name indicates, NNI seeks to find the observation in the dataset most similar to the observation for which some data is missing. The observation containing the missing value is called the recipient, and the nearest neighbor is the donor. Note that the roles may be reversed if the donor is missing a different value for which the recipient is populated. For the purposes of this thesis, this assumes that countries which are most similar according to a relatively large number of criteria will also be similar in those areas for which only one country has been assessed. Chapter 3 provides details on how NNI was implemented in this study.

In recent years, developments in computer software have made it possible to employ missing data techniques which are superior to those discussed earlier. The techniques themselves are not new, but their computational feasibility has recently become a reality (Allison, 2001: 2). Multiple Imputation with Data Augmentation is one such technique. Unfortunately, software constraints prohibited us from utilizing these methods; they are included in Chapter 5 as a possible area for improving on this effort through additional analysis.

2.4.1.3. Summary of Missing Data Discussion

Missing data is an issue that commonly occurs in the social science and other fields. While no technique could possibly perform better than actually finding the missing values, several techniques for dealing with missing data are available. For this thesis, Nearest Neighbor Imputation (NNI) was selected for its intuitive approach and ease of use. Chapter 3 provides details on the implementation of NNI.

2.4.2. Factor Analysis

Factor Analysis (FA) is a technique used to reduce the dimensionality of a set of data and explore relationships among its variables (Lattin *et al*, 2003: 127). It does this by grouping variables whose previous relationship was unknown through identifying underlying dimensions, or factors, reflected in those variables (Dillon and Goldstein, 1984: 53). The result of FA is often the identification of a small set of "unobservable characteristics" which explain a great deal of the information and variation present in the much larger dataset (Lattin *et al*, 2003: 128-129). Readers familiar with Principal Components Analysis (PCA) will find FA similar in solution methodology, though slightly different in underlying assumptions and interpretation. For our purposes, we assume that the observable data we have available are actually measurements of some unobservable characteristics such as State Stability. FA is designed to uncover the concepts or ideas that are truly of interest, but may not be directly measurable. Such a technique can be valuable for the purpose of understanding and condensing the myriad of data available on the nations of the world. This section provides an overview of FA as well as how it can be used for the purposes of assessing and comparing nations and identifying failing states.

2.4.2.1. Overview of Factor Analysis

When using FA, we assume that the variation in a variable within a dataset comes from two sources; the variance unique to that variable, and the variation that is common, or shared, among the several variables reflecting a common underlying factor (Dillon and Goldstein, 1984: 56). For this reason, FA is often referred to as Common Factor Analysis. The original indicator variables are then thought of as functions of these unobservable common factors (Dillon and Goldstein, 1984: 57). The purpose of FA is to identify this relatively small number of underlying characteristics and use these, or a subset of the original variables heavily loaded on them, as a substitute for the complete dataset for analysis and prediction.

The purpose and benefit of FA can be better understood through an example. Section 5.3 of Lattin *et al*., 2003 recounts a 1991 study investigating consumers' preference in breakfast cereals (Lattin *et al*, 2003: 147-153). Consumers rated 12 brands of cereal on each of 25 attributes. The purpose of the study was to predict which brands consumers would be more likely to purchase by considering a smaller number of underlying characteristics (much fewer than 25) represented in their ratings. The researchers used Factor Analysis to identify common factors which account for the majority of the variance in the original data. (Lattin *et al*, 2003: 148). Figure 2-3 presents a visual representation of their results.

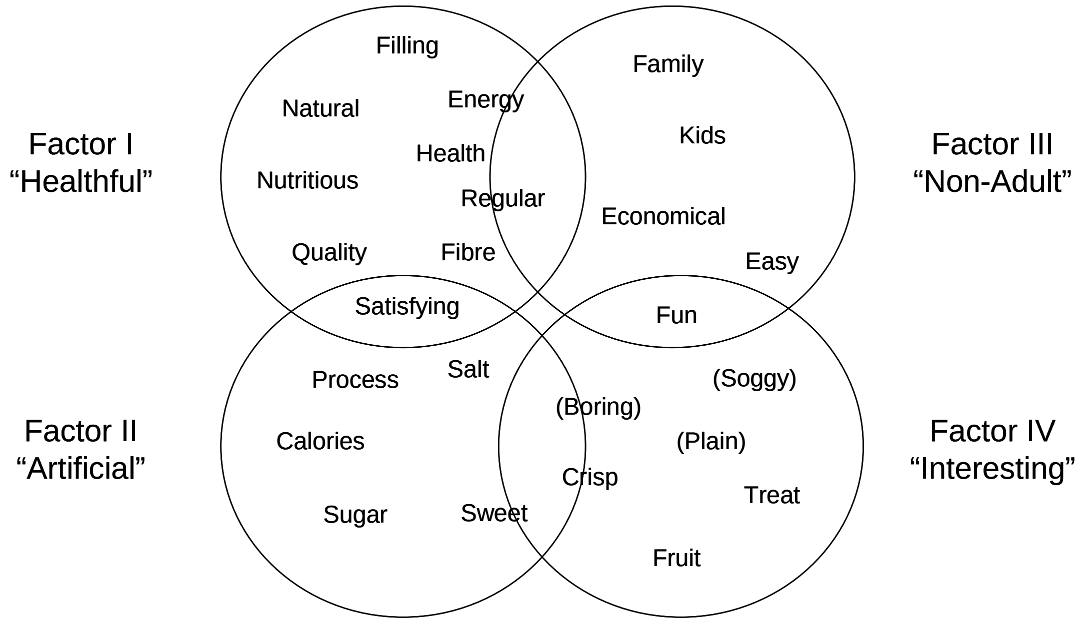

Figure 2-3: Results of Factor Analysis

Lattin's research team found that the original 25 variables could be represented to a large extent by four underlying dimensions which they chose to label "Healthful", "Artificial", "Non-Adult" and "Interesting". Each variable is presented as a member of the group of variables comprising each factor. Variables in parenthesis are negatively correlated with the factor scores, meaning, for example, that as sogginess of cereal increases, its "Interesting" score decreases (Lattin *et al*, 2003: 153). Their choice of factor labels may be debatable, however the benefit of the FA is clear: rather than needing to consider all 25 original attributes, we may be able to understand consumers' cereal preferences by looking at only the four latent factors reflected in those variables.

It is important to note that the common factors do not represent a mutually exclusive, collectively exhaustive representation of the original data. In other words, the underlying factors may overlap as shown in Figure 2-3 in the sense that attributes which are most associated with, or loaded on, one factor may also reflect variation in another. In addition, the four factors retained in Lattin's study only account for 52% of the total variation in the original data (Lattin *et al*, 2003: 149).

If an analysts desires, he may retain more common factors to account for more of the variation in the data. It is to some degree an art form deciding how many common factors are sufficient to characterize the data. However, it is generally acceptable to only retain common factors which "account for at least as much variation as one of the original variables in the analysis…" (Lattin *et al*, 2003: 148). Once the amount of variation explained by a factor falls below that of the original variables, it ceases to provide a significant improvement to the model.

2.4.2.2. Using Factor Analysis to Identify Failing States

Recall that two primary objectives of Factor Analysis are to reduce the dimensionality of a dataset and explore relationships or commonalities among the different variables (Lattin *et al*, 2003: 127, Dillon *et al* 1984: 53). For the purpose of predicting failing states, if we were somehow able to produce a single yardstick with which we could measure the probability of a state collapsing, we would have no need for exploratory analysis. As described in the first portion of this chapter however, there is no single agreed upon measure which can predict with any degree of accuracy when and if a state will decline into failure. On the contrary, there are numerous studies on the subject, all of which cite different variables as indicators of impending state failure. Table 2-1 shows a list of variables experts use for the purpose of predicting states in crises. This list is not intended to be exhaustive, but rather a compilation of variables encountered in the scholarly literature. The bibliography includes more detailed citations. This table includes many variables used to predict crisis or state failure. Often, variables hypothesized to be useful for such predictions are chosen as much on the basis of the availability of the data as the true expectation of their importance. Once again, if an accurate attribute “Probability of Collapse” was readily available for each state, further study would not be necessary. As it is, we are left to do what we can with the data that is available. In this thesis we have used Factor Analysis to gauge the immeasurable Probability of Collapse or Crisis Level, as they are reflected in the myriad of variables currently available.

Table 2-1: Variables Considered by Subject Matter Experts for Identifying Nations in Crisis

Repressive Government [1,2,4,5,6,7,9,10,11,13]	GNP/GNI - Per Capita [4,12]
Ongoing/Recent Violent Conflicts [1,2,4,5,8,9,10,13]	Imports ($) [1,3]
Representative Government [2,4,5,6,7,9,11,13,14]	Imports other than Money [1,3]
Stable Government [1,2,6,7,8,10,11,13]	Private Armies [1,8]
Cultural Factions [1,2,5,6,7,10,11]	Proximity to "Bad Neighbors" [2,7]
Economic Trade [1,4,5,6,8,12,14]	Refugee/Displaced Population [4,13]
Infant Mortality Rate [3,4,5,12,14]	Rising Standard of Living [1,2]
Legitimate National Security Force [6,7,8,9,10]	Stable Infrastructure [2,6]
Personal Freedom [1,2,4,5,6]	Useable Land and Land Disputes [2,13]
Religious Factions [1,2,5,6,7]	Water/Sanitation [3,13]
Corrupt Government [1,2,8,10]	Annual Food Production Change [4]
GDP - Per Capita [4,5,9,14]	Battle Deaths [4]
GDP Growth Rate [4,9,13,14]	CO2/CFC Emissions [3]
IMF Involvement - Foreign Aid [1,2,3,4]	Condom Use [3]
Poverty Rate [1,3,7,13]	Consumer Price Index [4]
Publicly Accepted Constitution [1,2,6,8]	Exports other than Oil [1]
Unemployment Rate [1,2,3,13]	Forest Area [3]
Unmet War Goals [7,8,10]	Former British Colony [9]
Caloric Intake [3,4,5]	Immigration [2]
Education [2,3,13]	Income Inequality (GINI) [4]
Life Expectancy [1,5,12]	Inflation [2]
Literacy [2,3,12]	Maternal Mortality Rate [3]
Mass Murder Rate [1,4,6]	Military Spending - % of GNP [4]
Population Growth Rate [2,9,13]	Murder Rate [1]
Ratio of Population age 15-29 / 30-54 [3,5]	Per Capita Income [1]
AIDS [1,3]	Pollution [1]
Crime Rate [1,8]	Population [9]
Disease prevalence - Immunization [1,3]	Recognized Stable Borders [10]
Drug Traffic [1,7]	Suicide Rate [1]
Energy Demand [1,3]	Telecommunications [1]
Equal Rights for Women [2,3]	Terrorism Incidents/Population [1]
Exports ($) [1,3]	Tuberculosis [3]
Free Press [2,11]	Underweight Children [3]
Globalization Factor [1,2]	US military Intervention [1]

Sources: (see bibliography for detailed citations)

1 Barnett (2005) Blueprint for Action	8 Dziedzic *et al*. (2005) Quest for Viable Peace
2 Brown (2001) Causes of Internal Conflict	9 Poe *et al*. (2006) Journal of Conflict Resolution
3 UN Millennium Development Goals	10 Van Evera (2001) Hypotheses on Nationalism and War
4 Nafziger *et al*. (1997) War Hunger and Displacement	11 Snyder *et al*. (2001) Nationalism and the Marketplace of Ideas
5 O'Brien (2002) Forecasting Country Instability	12 Stewart (2002) Root Causes of Conflict in Developing Countries
6 DoD Directive 3000.05 (2005)	13 Rotberg (2004) When States Fail: Causes and Consequences
7 Durch (2002) Briefing to CJCS	14 Esty *et al*. (2006) State Failure Task Force Report

2.4.3. Discriminant Analysis

Discriminant Analysis (DA) is a technique used to partition a set of subjects into two or more disjoint groups (Lattin *et al*, 2003: 426, Dillon *et al*, 1984: 360). It does this by using information captured in a set of independent variables to create the clearest possible separation among the subjects, and assigning them to their most likely group (Lattin *et al*, 2003: 426).

The primary objective of DA is to classify or discriminate among individuals or objects (Dillon *et al*, 1984: 360). If we know what distinguishes members of various groups from one another, we may use this knowledge to assign new subjects to groups, or to predict future events based on a historical record of behavior of members of a certain group (Dillon *et al*, 1984: 363-4). In essence, this definition of Discriminant Analysis is equivalent to political or social discrimination, which is assigning often intangible traits or expectations to people based on measurable qualities such as race or gender.

The goal of this thesis is to assist analysts in determining which states are most likely to fail or erupt into violence unless some intervention occurs. Therefore, if we consider "failing states", "borderline states", and "stable states" as three mutually exclusive, collectively exhaustive groups into which all nations can be classified, DA may be a useful tool for this research. The idea is to find the linear combination of the set of independent variables collected on all countries that produces the largest possible distinction between the three classifications (Lattin *et al*, 2003: 429). Once this relationship is determined, the linear combination can be used to classify previously unanalyzed states, or the same states at various points over time. Chapter 3 explains how DA was implemented in this study; the reader is also referred to *Analyzing Multivariate*

Data (Lattin *et al*, 2003) or *Multivariate Analysis* (Dillon *et al*, 1984) for detailed discussion of the uses, assumptions, and mechanics of DA.

2.4.4. Summary of Techniques

The majority of recent work in predicting failing states is centered on using Ordinary Least Squares Regression, sometimes with variable transformations. However, such efforts require a well-defined and quantifiable crisis level to be known for each state in advance of model construction, and defining such a value has proven quite difficult for researchers. In contrast, Exploratory Factor Analysis can reduce the dimensionality of currently available data and characterize the immeasurable, underlying factors reflected in it. Correlations between these factors and the initial variables can identify which subset of variables captures a significant amount of the total information. Discriminant Analysis can then be performed on the full or reduced dataset in order to classify countries into similar groups, and comparisons of these groups with those provided by subject matter experts will serve to identify the most critical nations. These techniques are not proposed in order to refute other models found in the literature, but rather to augment or validate ongoing crisis prevention efforts.

2.5. Chapter Summary

Many analysts and organizations are attempting to predict failed or failing states using mathematical modeling. The reasons for each study vary, but from a Department of Defense standpoint, failing states provide safe havens and recruitment pools for terrorist organizations. It is our national interests to identify failing states and, if possible, prevent them from collapsing. This thesis assists in that endeavor using appropriate analytical techniques.

3. Methodology

3.1. Introduction

This chapter describes the analysis techniques used in this study to identify unstable or failing states. It begins with a description of how variables were chosen for initial consideration. Next, it discusses the methods used to reduce and refine the set of selected variables, and for dealing with missing data. The chapter concludes with an explanation of the process used to select variables most critical for the purposes of identifying unstable nations, and classifying states as critical or failing.

3.2. Data

A primary purpose of this study is to identify a relatively small set of key variables, available through open source, which could be used to classify states in terms of their overall stability. These variables may then be used to determine which states are most likely to fail, or otherwise experience some form of crisis. As explained in Chapter 2, various subject matter experts (SME) and organizations use a myriad of variables for just such a purpose. This section describes our methods for building our initial dataset, and the preliminary steps used to reduce the number of variables. Our technique for dealing with missing data is also discussed.

3.2.1. Initial Dataset

Our data collection began by exploring the scholarly literature for any variables SME considered relevant for the purpose of identifying failing states. A list of these variables served as a minimum amount of data to be analyzed in this study. In addition to the SME identified variables, any other variables encountered during the search, and any we could reasonably expect to contribute to the model, were included in our initial dataset as well. Table 2-1 provides a summary of SME variables used, and Appendix A for a list of all variables collected.

In all, 167 variables were collected for consideration. However, several of these variables were not unique. For example, Gross Domestic Product (GDP) Per Capita was collected from both the World Bank and United Nations Statistic Division. Both were included in the initial dataset for two main reasons. First, since data was collected indirectly through open source, not directly by our team, comparing several like variables could serve to validate the data and improve confidence in it. Second, as data needed to be copied, pasted, moved and in some cases transformed or calculated several times throughout the database construction process, two previously identical variables suddenly appearing different would signal that a computation error may have been made. In other words, retaining two identical variables from different sources served as an error check for both our work, and the various agencies from which our data was drawn.

Clearly, 167 variables could not possibly encapsulate everything about the status of a country. Fensterer, compiling the work of a number of authors, outlines 44 broad categories for assessing state stability (Fensterer, 2007). Each of these categories, for example Judicial Effectiveness, may require dozens of variables collected over time to truly gain a perspective on each nation's status. However, there is a large gap between what is needed to fully assess state stability and what is currently being collected and made available. Table 3-1 divides the multinational data into four main categories based on a specific variable's importance in assessing state stability and the level at which the data is available from open sources.

Table 3-1: Data Collection Focus

	Importance in Predicting State Failure	
Availability	Significant	Insignificant
Collected and Readily Available	Most useful in predicting failing states. Collection efforts should be continued and refined as necessary.	Marginal benefit gained. Data collection resources may be available to drawn upon for other purposes.
Not Currently Collected	Intelligence requirement. Should develop metrics and begin data collection for comprehensive assessment.	Initiating collection efforts unlikely to provide additional benefit.

The focus of this thesis is to consider all currently available open source variables and determine which are truly significant for our purposes. The reader is encouraged to refer to Fensterer's work and the Iraq Study Group Report published in November, 2006 for analysis of the types of variables which, if collected, may provide an even more comprehensive assessment of state stability.

Once the initial dataset was finalized, the process of data reduction began. Recall that one of the hypotheses of this thesis is that adequate classification of failing states is possible with as few as ten open-source variables. The next section describes the first step in moving toward that goal.

3.2.2. Reduced Dataset

Our initial dataset represented a collection of data in three major dimensions: countries, years, and variables. We collected data on 242 countries from 1995-2005 across 167 variables. Unfortunately, only about 51% of the database was populated. This section describes the methods use to generate a single, fully-populated dataset for further analysis.

3.2.2.1. Removal of Countries

Of the 242 countries comprising our initial study, 42 were removed on the basis of their lack of available data, or the fact that the country no longer exists. None of these countries' records were populated with more than 20% of the variables in the dataset. Many were small island states or recent protectorates. It is our contention that the removal of these countries did not materially impact the usefulness of this study; however the omitted countries are provided here for informational purposes.

Table 3-2: Countries Removed From Study

Abkhazia	Glorioso Islands	Reunion
Akrotiri	Greenland	Saint Helena
American Samoa	Guadeloupe	Saint Pierre and Miquelon
British Virgin Islands	Holy See	South Georgia
Channel Islands	Isle of Man	Spratly Islands
Christmas Island	Martinique	Taiwan
Cocos (Keeling) Islands	Mayotte	Tokelau
Cook Islands	Monaco	Turks and Caicos Islands
Dhekelia	Montenegro	Tuvalu
Europa Island	Montserrat	US Virgin Islands
Falkland Islands	Nauru	Wallis and Futuna
Faroe Islands	Niue	West Bank (Combined w/ Gaza Strip)
French Guiana	Northern Mariana Islands	Western Sahara
Gibraltar	Pitcairn Islands	Yugoslavia

If subject matter experts determined that some or all of these nations were of political interest, the methodology proposed here could be utilized, provided requirements were created to collect the necessary data.

3.2.2.2. Reduction in the Number of Years Analyzed

Several variables, such as Net Migration Rate, have historically only been collected every few years. In addition, even if a data collection agent collects data annually, not every country is assessed every year. For this reason, a look at any individual year would result in no less than 44% missing data, which is the amount missing from the 2004 dataset. Of course, if the data were never collected, it is virtually impossible to go back and accurately and directly fill in the missing values. However, there are methods for dealing with such an issue.

The focus of this thesis is on the identification of key variables that may be used to identify failing states. The underlying assumption here is that the relationship among, and the importance of, each of these key variables remains relatively constant over time. Therefore, for this initial analysis, the most recent data available for each country was used. This had the effect of reducing the amount of data we would need to impute to less than 20%. However, as is recommend in Chapter 5, it would certainly be useful to investigate a process for imputing data which is missing for some, but not all, years. Such a technique would allow time-series analysis of the data, which could prove more useful for prediction, as opposed to classification, of failing states.

3.2.2.3. Variable Reduction

As mentioned earlier, several of the 167 initial variables were essentially identical in that they measured exactly or nearly the same thing, but were possibly collected by different sources, perhaps using differing methods. However, even two distinct variables can be redundant. Multicollinearity occurs when one or more of the independent variables are correlated. If the correlation is high or a combination of variables are linearly dependent, the variables are capturing related variance. It can also occur if one of the variables is close to a linear combination of one or more of the others. With the large number of variables in our initial dataset, a high degree of multicollinearity is virtually guaranteed. Therefore, the first step in reducing the dataset was to remove at least one of every two variables shown to be highly correlated.

Before continuing on, several comments on the necessity of this step are in order. As described in Chapter 2, Factor Analysis is our preferred method for reducing the dimensionality of a dataset. It has the benefit of being robust to multicollinearity, and incorporates information from each variable, minimal though it may be. However, there are several reasons to reduce the number of variables prior to performing FA.

First, Appendix A shows a gross measure of data availability for each of the initial variables. The percentage shown is the proportion of countries for which at least one value was collected on that variable between 1995 and 2005. Because of the significant amount of missing data in our dataset, values would need to be imputed in order to accomplish some of the other techniques used later such as Factor Analysis and Discriminant Analysis. However, each time data is imputed, some amount of additional uncertainty is generated. This uncertainty biases the model and is not directly reflected in the results. Therefore, if we are able to propose reasonable justification for discarding variables with significant amounts of incomplete data, unnecessary uncertainty can be avoided.

Second, most data imputation techniques, such as the Nearest Neighbor method used in this study, assume the data is normally distributed, and provide better substitute values if that assumption is met. Furthermore, when using Linear Discriminant Analysis, optimal results are only attained if the independent variables are normally distributed (Dillon *et al*, 1984, 379). Therefore, each variable included during these steps would need to be checked individually for normality prior to analysis, and transformed as appropriate. Obviously, provided no material information would be lost, a smaller set of variables to examine and test was desirable.

Finally, while Factor Analysis does reduce the dimensionality of the data, to truly understand the underlying structure the analyst must characterize each of the latent factors. This is typically done by considering which variables are most heavily loaded on each of the factors as seen in the cereal example in Chapter 2. This process is considerably more involved when an extremely large number of variables is used.

For these reasons, we examined the correlation between each pair of variables in the initial dataset. The Pearson correlation coefficient of any two variables *x* and *y* represents the degree of linear dependence between the two and can be computed by

$$\rho = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}}$$

and $-1.0 \leq \rho \leq 1.0$. Values close to +1 suggest high positive correlation, meaning as *x* increases, *y* increases. Values close to -1 indicate negative correlation in which as *x* increases, *y* decreases. Values of ρ near zero indicate no correlation (Wackerly *et al* 2002: 251).

A portion of the resulting correlation matrix is shown in Table 3.3, with significant correlation values highlighted.

Table 3-3: Sample from Variable Correlation Matrix

	A110	A111	A112	A113	A114	A115	A116	A117	A118	A119
A131	0.051	0.586	-0.631	0.271	0.355	0.030	-0.209	-0.020	-0.017	0.350
A132	0.419	0.599	-0.613	0.105	0.165	0.237	-0.282	-0.103	-0.126	**0.835**
A133	0.046	0.010	0.041	-0.043	-0.114	0.154	0.020	0.002	-0.035	0.127
A134	0.689	0.351	-0.385	0.074	0.120	0.095	-0.169	-0.092	-0.006	0.341
A135	0.080	0.143	-0.186	-0.088	0.036	**0.815**	-0.321	-0.142	-0.205	0.211
A136	-0.176	-0.152	0.135	0.028	-0.053	-0.121	0.214	0.148	0.153	-0.139
A137	0.045	0.437	-0.430	0.086	0.172	-0.159	0.089	0.037	0.181	0.472
A138	-0.116	0.429	-0.358	0.208	0.091	-0.171	0.164	0.299	0.042	0.134
A139	-0.165	**-0.712**	**0.823**	-0.272	-0.369	-0.202	0.268	0.013	0.064	0.022
A140	0.203	**0.789**	**-0.798**	0.212	0.309	0.251	-0.337	-0.128	-0.144	**0.765**
A141	0.064	-0.486	0.516	-0.140	-0.320	-0.050	0.136	-0.068	-0.025	-0.314
A142	-0.086	-0.045	-0.196	-0.204	-0.141	0.113	-0.229	-0.110	-0.068	0.031
A143	0.174	0.656	-0.630	0.213	0.229	0.135	-0.228	-0.086	-0.079	**0.973**
A144	-0.189	-0.051	-0.121	0.020	0.025	0.124	0.178	0.161	0.303	0.041
A145	0.207	0.669	-0.637	0.212	0.233	0.148	-0.226	-0.107	-0.060	**0.961**
A146	0.298	**0.760**	**-0.730**	0.231	0.283	0.223	-0.263	-0.117	-0.059	**0.934**
A147	0.213	0.627	-0.573	0.175	0.226	0.067	-0.183	-0.079	-0.040	**0.935**
A148	0.067	0.485	-0.648	-0.168	0.198	0.254	-0.275	-0.115	-0.154	0.403
A149	0.126	**0.769**	**-0.788**	0.372	0.373	0.176	-0.249	-0.130	-0.054	0.477

Note that variable names were coded for space and software integration purposes. Appendix A contains a complete listing of variables and codes. From the matrix we see, for example, that variable A119, which is GDP Per Capita appears, to be highly positively correlated with several variables including A132, Electric Power Consumption. In addition, A111, Caloric Intake is negatively correlated with A139, Number of Births per Woman. Other correlations are less direct, such as the high positive correlation between A111 and A140, Caloric Intake versus Number of People per 1,000 with Fixed-line or Mobile Phones.

Values above 0.7 (or below -0.7) indicated that at least 70% of the variation in one variable could be represented by the other. Therefore, at least one of these variables was removed. For cases in which several variables were all highly correlated with each other, only one variable was retained. The 0.7 cutoff was a subjective choice. Figure 3-1 shows the number of correlations present as a function of the cutoff value chosen. As the threshold for significant correlation decreases, the number of variables to be discarded grows exponentially.

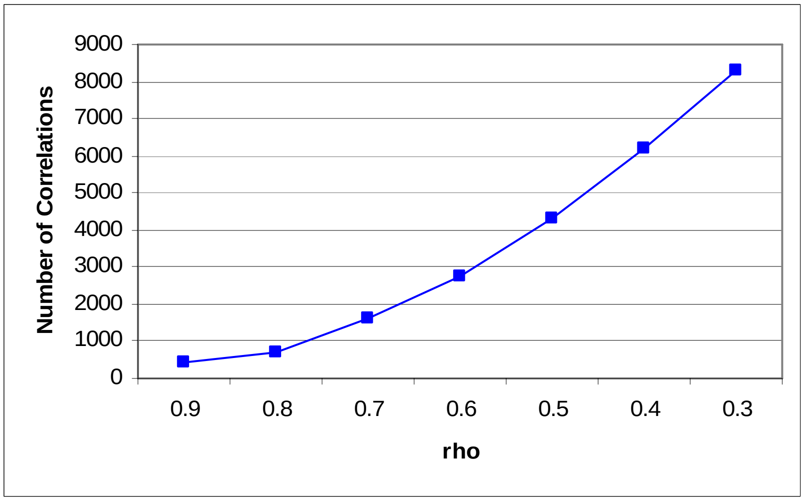

Figure 3-1: Number of Correlations as a Function of Threshold

In deciding an appropriate value to use as a cutoff, we needed to strike a balance between the gains and losses associated with removing variables from our model. Removing superfluous data would significantly decrease computation and interpretation time in later steps, and limit the uncertainty introduced during imputation. On the other hand, prematurely disregarding variables may result in a loss of important information. In addition, FA will be used to further reduce the number of variable dimensions, so it is not necessary to remove every instance of multicollinearity during this step. In order to retain as much information as possible, it would be better to err on the side of choosing too high a threshold for removal. The 0.7 threshold seems to have provided the appropriate balance, as evidenced by the number and breadth of variables retained.

Using 0.7 as a threshold, the number of variables carried forward was reduced from 167 to 60. In almost all cases, each variable removed was still represented in the reduced dataset not only by at least one highly correlated variable, but also one that seemed to be an intuitive proxy for the removed variable. For example, Pupil-Teacher Ratio – Primary Level was replaced by Pupil-Teacher Ratio – Secondary Level. The 60 remaining variables still represented a much greater number than any model found in the literature, which further suggested that the 0.7 value was not too low.

When a discrepancy existed in the amount of data available for two highly correlated variables, the variable with more missing data was discarded. This approach improved the average percentage of available data per retained variable from 81% to 85%, and the variance in the amount of data present decreased by 18%. The list of variables retained for the reduced dataset can be found in Appendix B.

3.2.3. Variable Transformation

Once the variables to be used for the remainder of the study were selected, the distribution of each variable was examined for gross violations of the normality assumption. If a variable did not appear at least approximately normally distributed, as discussed earlier we could transform it to improve the results of the data imputation and Discriminant Analysis. The following is in example of the variable transformation process used in this study.

On of the simplest ways to check for normality in a variable is simply to plot a histogram of the data. Figure 3-2 shows a histogram of the Population Density of the nations of the world in thousands of people per square mile.

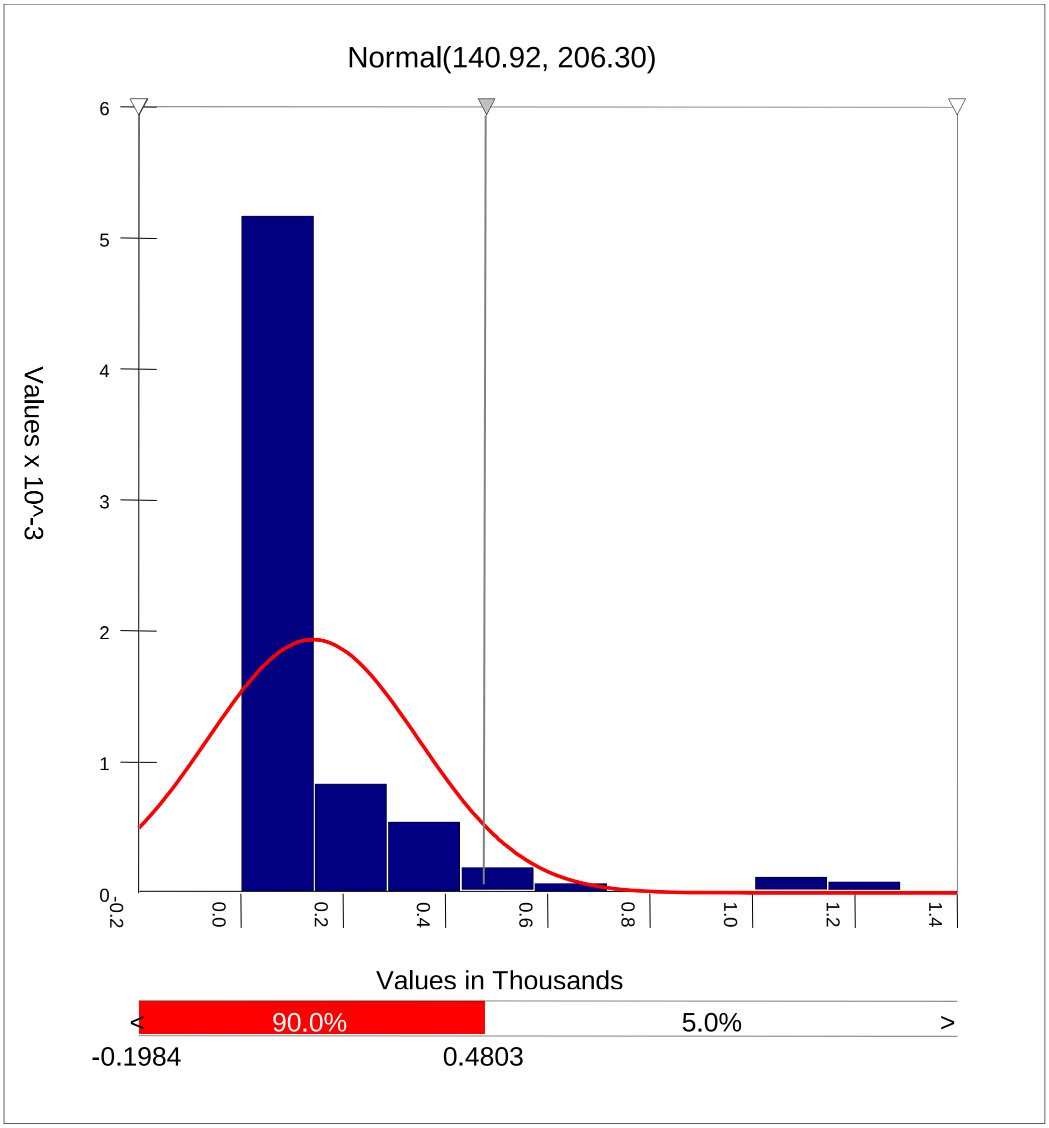

Figure 3-2: Histogram of Population Density Data Before Transformation

Clearly, the data do not appear normal. More formally, three common Goodness-of-Fit (GOF) tests can be run on the data to see if the hypothesis that the data do come from a normal distribution can be rejected. They are the Chi-Squared, Anderson-Darling, and the Kolomogorov-Smirinov tests.

The Chi-Squared Statistic is the most popular Goodness of Fit Test. It separates data into K groups or bins and compares the number of entries in each bin with the number one would expect to be in each if the data were distributed according to the distribution being test, in this case the normal distribution. The Chi-Squared Test Statistic then is

$$\chi^2 = \sum_{i=1}^{K} \frac{(N_i - E_i)^2}{E_i}$$

where K is the number of bins, N_i is the *observed* number of entries in the i^{th} bin, and E_i is the *expected* number of entries in the i^{th} bin, given a normal distribution. Notice that as the difference between the observed and expected values increases, the Chi-square test statistic increases. Thus if this difference is sufficiently large, we may conclude that the true distribution of the data is not normal.

The Anderson-Darling (A-D) test uses the following test statistic to determine if the data come from the hypothesized cumulative distribution function (cdf)

$$A^2 = -N - S$$

where

$$N = \text{sample size}$$

$$S = \sum_{k=1}^{N} \frac{2k-1}{N} [\ln \hat{F}(Y_k) + \ln(1 - \hat{F}(Y_{N+1-k}))]$$

$$Y_k = k^{th} \text{ ordered data point of Y}$$

$$\hat{F} = \text{hypothesized cdf}$$

Again, larger values of this statistic indicate violations of the normality assumption.

The final test for normality is the Kolomogorov-Smirinov (K-S) Test, which uses a more simple test statistic

$$D = \max[| F_n(x) - \hat{F}(x) |]$$

where

$$F_n(x) = \frac{number\ of\ \ ordered\ observations\ below\ x}{n}$$

and

$$\hat{F}(x) = \text{hypothesized cdf}$$

The K-S test measures the value of the greatest discrepancy between the observed and the hypothesized, in this case the normal, cdf.

All three tests can be used to test the same hypotheses:

Ho: The data are drawn from a normal distribution

Ha: The data are not drawn from a normal distribution.

The results for the raw Population Density data are provided in Table 3-4.

Table 3-4: GOF Test Results for Non-Transformed Data

	Chi-Square	A-D	K-S
Test Statistic	231.43	20.93	0.25
P-value	0.0000	< 0.005	< 0.01

Here, the p-value represents the probability that a sample of the same size drawn from the hypothesized normal distribution could generate a test statistic as high as the one observed. We see that there is essentially zero likelihood that the observed Population Density data came from a normal distribution, and we should reject the null hypothesis.

To remedy this, we attempt to transform the variable in such a way that the resulting values more closely follow a normal distribution. In the case of Population Density, taking the natural logarithm of the values produced the distribution shown in Figure 3-3.

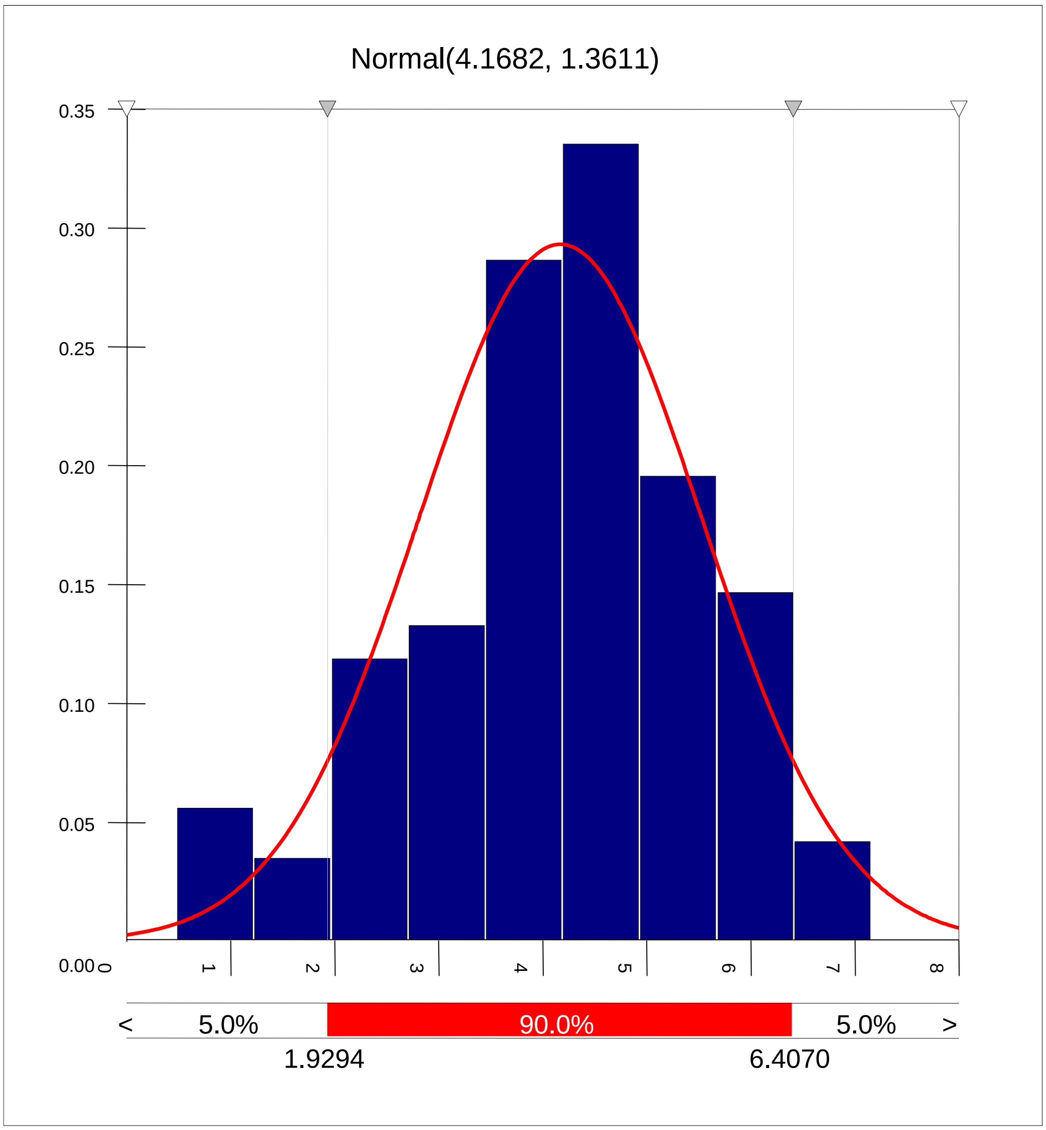

Figure 3-3: Histogram of Population Density Data After Transformation

Visually, it appears at least plausible that the transformed data follow a normal distribution. Running the aforementioned tests again produced the following results:

Table 3-5: GOF Test Results for Transformed Data

	Chi-Square	A-D	K-S
Test Statistic	14.28	1.00	0.07
P-value	0.4291	< 0.025	< 0.01

Each of the test statistics were dramatically reduced when using the transformed data. While the A-D and K-S tests still do not support such a claim, the Chi-square test allows a 43% chance that the data observed came from a normal distribution. The Chi-square test can be considered valid if the expected bin frequencies are sufficiently large, typically greater than five (Banks *et al*., 2005: 327). Dividing the range of the data into 15 bins of equal probability, each bin has an expected frequency of 12.93, which is sufficient. For our purposes, the transformed data will be used as it is much closer to the desired distribution than the raw data. Appendix B lists the transformation used for each of the variables in the reduced dataset.

3.2.4. Missing Data Imputation

As discussed in Chapter 2, there are several methods for dealing with missing data. For this thesis, we used a Nearest Neighbor Hot Deck Imputation (NNI) available in the statistical package XLSTAT. This procedure replaces missing values for a given record with values observed for a similar record, the nearest neighbor. A complete imputed dataset is then output for future analysis.

To find the nearest neighbor to country *x*, the distance in the variable space between it and every other country *y* on the basis of the 60 variables is calculated using the Euclidean Distance formula

$$D_{x,y} = \sqrt{\sum_i (x_i - y_i)^2} \qquad i = 1 \text{ to } 60$$

For cases in which multiple variables are missing for two observations, the average of the distances between each of the non-missing variables is substituted for the missing distance values. In the end, each country is assigned a rank order of its nearest neighbors. If a state is missing a value on one of its variables, a value was imputed from the most similar country having a value on that variable.

With the data imputation, the dataset used for the remainder of this study was workable. Appendix B provides a list of the variables considered, and Appendix C lists the countries analyzed. The next step was to determine which variables in the dataset were most significant for characterizing nations.

3.3. Variable Selection

This section provides the methodology used to achieve the first of the two primary goals for this thesis – identify a set of key variables which can be used to classify weak or failing states. We used two overarching methods for variable selection; Factor Analysis, and the model construction procedures within Discriminant Analysis. The variables selected using each method, and the resulting discriminant functions can be found in Chapter 4.

3.3.1. Factor Analysis

Using FA to identify key variables in a dataset involves two primary steps. First, we identify the principal factors characterizing the latent structure of the data. A relatively small number of principal factors accounts for the majority of variation in the entire dataset. Second, we examine these factors, label them, and select those variables which load most heavily on the key factors. For this study, we used three different techniques for selecting variables to be used for classifying states based on factor scores.

Technique 1 was simply to discriminate based on each country's factor scores across all factors. This is equivalent to using the factor scores as observable variables. This technique has the benefit of including as much information as possible from the original dataset, but is less useful in the sense that all 60 variables are required to generate these scores. Technique 2 was to choose those variables most heavily loaded on the first and second principal factors. These factors would account for the majority of the variation described by the entire set of factors. The third technique used was to choose at least one variable from each of the retained factors.

3.3.1.1. Mechanics of Factor Analysis

This section provides the mechanics involved in FA. It is compiled from Dillon and Goldstein, 1984 and Lattin, Carroll and Green, 2003. Further details on FA can be found in either of these texts.

For illustrative purposes, assume we have a dataset X with i observable variables. FA assumes that the variation in each variable X_i is attributable to two sources, that which is inherent in the variable denoted δ_i and that which can be attributed to some number of common factors ξ. If we assume a two factor model is hypothesized, then the observed value for each of the variables could be written as

$$X_i = \lambda_{i,1}\xi_1 + \lambda_{i,2}\xi_2 + \delta_i$$

where the λ's are the coefficients which reflect the variation attributable to each of the common factors (Lattin *et al*, 2003: 133). Thus, if we hypothesize that a country's Infant Mortality Rate (IMR) is really a function of two immeasurable factors such as National Economy and Health Services, we could predict a given country's IMR if we knew these factor scores. However, in FA we have the observed data; what we are interested in is discovering and characterizing the latent factors which resulted in the data observed.

To find these common factors, we begin with the correlation matrix R, made up of all correlations between each pair of variables. We are now interested in determining if there are one or more underlying factors such that these correlations fall to zero if the variation attributable to such factors is removed. That is, does the following equation hold for some ξ (Dillon *et al*, 1984: 64-65)?

$$\rho(X_i, X_j \mid \xi) = 0 \quad i \neq j$$

If so, then a set of common factors ξ must exist such that the equation for X_i above is true.

If we now assume that the portions of the variation common to the underlying factors and unique to the variable itself are uncorrelated, and we standardize the ξ so that their mean is 0 and standard deviation is 1, we can express the variance of any X_i as

$$\mathrm{var}(X_i) = \mathrm{var}(\sum \lambda_i \xi_i) + \mathrm{var}(\delta_i)\,.$$

The first term on the right is the variance in X_i attributable to the common factors. This is also known as the communality of X_i, and is often denoted h^2_i. These communalities are then used to construct our reduced correlation matrix (Dillon *et al*, 1984: 66-67).

Since FA is concerned with the variation in observed data attributable to common factors, we need to include some measure of the covariance along with the correlations. To do this, we replace the diagonal elements of the correlation matrix R with an estimate of each variable's communality. The method for estimating the initial communalities used in this thesis is the Squared Multiple Correlation (SMC). This value is found by regressing each variable on all other variables in the dataset one at a time, and calculating the resulting R-square value (Lattin *et al*, 2003: 136-7). Of course, we would like to regress each variable on the common factors. However, we do not have the common factors at this point, only the variables reflecting these factors. Instead, we use the SMC which provides a lower bound for the true communalities (Lattin *et al*, 2003: 137). Recall that in linear regression, R-square represents the amount of variation in a variable attributable to the variation in the others. Thus our reduced correlation matrix is

$$R^* = \begin{bmatrix} R_1^2 & \rho_{(2,1)} & \cdots & \rho_{(1.p)} \\ \rho_{(2,1)} & R_2^2 & & \\ \vdots & & \ddots & \\ & & & \\ \rho_{(p,1)} & & & R_p^2 \end{bmatrix}$$

The first common factor can now be calculated by computing the eigenvalues and eigenvectors of R^*. The largest eigenvalue will be ξ_1. In addition, the total amount of variance in the original dataset captured by this first factor can be found by multiplying the first eigenvector by its transpose (Dillon *et al*, 1984: 74). The eigenvalues and corresponding eigenvectors are all (λ, u) solutions to

$$R^{*}u = \lambda u\,.$$

Finding solutions to this equation requires finding roots to a polynomial of order p. This can be accomplished using computer-run algorithms which estimate numerical solutions.

To find the next factors, we subtract ξ_1 from R^* and compute the eigenvalues again. This process continues until the largest eigenvalue no longer accounts for a significant amount of the remaining variation in the data. A common rule of thumb is to extract only those factors with eigenvalues greater than or equal to one.

At this point, we could be satisfied with a set of previously unmeasured factors which account for a significant amount of the variation in a dataset. However, we can improve on the estimation of these factors in two ways.

First, recall that the communalities used to construct the original reduced correlation matrix were estimated through regression. But what we are interested in is the true communality - the amount of variation in each variable attributable to the common factors. We can improve on our initial estimates by examining the correlations between the original variables and the common factors we have just calculated based on our initial communality estimates. These correlations are also called factor loadings (Lattin *et al*, 2003:136). For example, consider a model in which only two factors are retained. If the variable X_1 is found to have loadings of 0.77 and -0.24 with the first and second principal factors respectively, R^2_1 would be replaced by $(0.77)^2 + (-0.24)^2 = 0.65$ in the new reduced correlation matrix, and we proceed as before. This iterative process continues until there is very little change in communality estimates (Lattin *et al*, 2003:136). Typically, software packages perform this process automatically so the there is no need to run FA multiple times.

A second technique for improving our factor model does not deal as much with determining the underlying structure of the data, but rather with interpreting the structure. Factor Rotation involves reorienting the principal factors in such a way that the original variables, to the extent possible, become more heavily loaded on one factor than the others. The desired results of such a rotation are described in Lattin *et al*, 2003 page 139:

1. Most of the loadings on any specific factor (column) should be small (as close to zero as possible), and only a few loadings should be large in absolute value.
2. A specific row of the loadings matrix, containing the loadings of a given variable with each factor, should display nonzero loadings on only one or no more than a few factors.
3. Any pair of factors (columns) should exhibit different patterns of loadings. Otherwise, one could not distinguish the two factors represented by these columns.

A common rotation technique, and the one used in this thesis, is Kaiser's Varimax Rotation. We define the elements of the loadings matrix Λ derived from the FA procedure as r_{ik}, equal to the correlation of variable i with common factor k. Then the proportion of variation in variable i which is attributable to k is $(r_{ik})^2$, also known as the communality of i, and the total communality of the factor model is the sum of these individual communalities. Our goal in rotating the factors is to find a rotation matrix T which yields a new loadings matrix A such that $A = \Lambda T$ and, to the greatest extent possible, the elements of A, a_{ik}, are such that $(a_{ik})^2$ is close to 1 (or -1) or zero (Lattin *et al*, 2003:145).

To accomplish this, we maximize

$$V = \sum_{k=1}^{c} \sum_{i=1}^{p} a_{ik}^{4} - \frac{1}{p} \sum_{k=1}^{c} \left(\sum_{i=1}^{p} a_{ik}^{2} \right)^{2}$$

where

c = number of retained factors

p = number of variables in the dataset

a_{ik} *= correlation of the* i^{th} *variable with the* k^{th} *rotated factor*

(Lattin *et al*, 2003:145).

The result of the Varimax Rotation may be better understood visually. In figure 3-4, the graph on the left shows a fictitious relationship between several original variables and two common factors which have not been rotated. The graph on the right shows their relationship after factor rotation. As you can see, although the structure of the data has not changed it should now be easier to characterize each of the factors because they are more closely related to quantifiable variables we have collected.

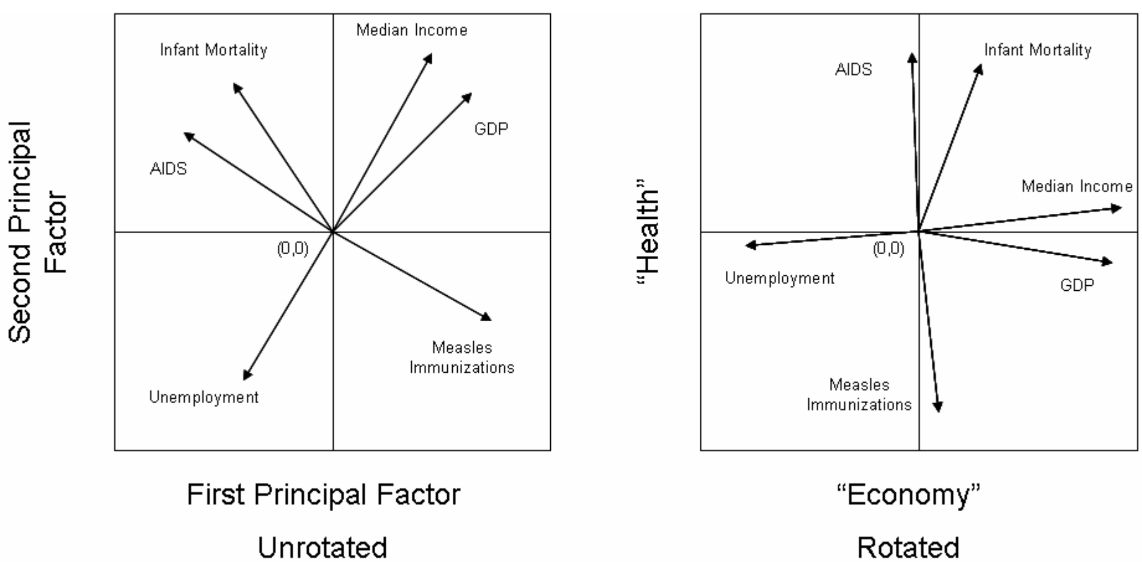

Figure 3-4: Conceptual Plot of Rotated and Unrotated Factor Loadings
(Lattin *et al*, 2003: 140)

Following FA and Rotation, we obtain a loadings matrix which provides the latent structure of our original dataset. As suggested by Figure 3-4, we can group variables by the principal factor on which they are most heavily loaded, and label the factors so that we may better understand the nature of the data. If we could measure each of these factors directly, we would be able to account for a significant proportion of the information available in the original, larger dataset with only a few variables. Recall, however, that the objective of FA is only to uncover the *immeasurable* factors reflected in the observable data. For practical purposes then, the next step is to select the variables we can measure which load on the principal factors in such a way that what they most closely approximate the structure of the data. We used two approaches to select variables based on factor loadings for this study. The first was to select at least one variable which loaded heavily on each of the retained factors, using a minimum loading of 0.5. This threshold indicates that at least half of the variance in a given variable can be attributed to the common factor. The second method was to choose all variables which loaded with a value of at least 0.5 on the most significant factors. Therefore, we chose variables in order of their loadings on the first principal factor until all scoring at least 0.5 were in the model. We then moved on to the next factor, and so on. As shown in Chapter 4, the two methods resulted in surprisingly similar sets of selected variables.

3.3.2. Discriminant Analysis

Discriminant Analysis (DA) finds the linear combination of the independent variables, or a subset of these variables, which produces the greatest difference between two or more predefined groups (Lattin *et al*, 2003, 429). As we have seen from our discussion of Factor Analysis, it may not be necessary to use the entire set of independent variables, particularly if the true differences among the groups lie in a smaller number of underlying dimensions. The following sections describe two ways we can choose the variables most useful in building the discriminant functions – Comparing Mean Differences in the Full Model and Stepwise Selection.

3.3.2.1. Full Model Variable Selection in Discriminant Analysis

We begin by considering the two-group problem for illustrative purposes. The results can be readily extended to the three-group situation used in this thesis, as will be described later. For a given set of variables X, we desire to find the vector of coefficients k to create the greatest difference in the discriminant function scores $t = Xk$ between members of the two groups (Lattin *et al*, 2003: 436-7). To measure this difference, we compare the sum of squares within each group to the sum of squares across all groups. We hope to simultaneously find the largest across-group variance and the smallest within-group variance which can be done by maximizing the ratio

$$L = \frac{SS_A}{SS_W}.$$

We calculate the sum of squares across groups by

$$SS_A = k'[n_1(\bar{x}_{(1)} - \bar{x})(\bar{x}_{(1)} - \bar{x})' + n_2(\bar{x}_{(2)} - \bar{x})(\bar{x}_{(2)} - \bar{x})']k$$

and the sum of squares within groups by

$$SS_W = \sum_i k'(\bar{x}_{i(1)} - \bar{x}_{(1)})(\bar{x}_{i(1)} - \bar{x}_{(1)})'k + \sum_i k'(\bar{x}_{i(2)} - \bar{x}_{(2)})(\bar{x}_{i(2)} - \bar{x}_{(2)})'k$$

where $\bar{x}, \bar{x}_1, and\ \bar{x}_2$ are the vectors of variable means for the entire sample, Group 1 and Group 2 respectively, and n_1 and n_2 are the size of the two groups. Rewriting our original objective function, we wish to choose k to maximize

$$L = \frac{k'[n_1(\bar{x}_{(1)} - \bar{x})(\bar{x}_{(1)} - \bar{x})' + n_2(\bar{x}_{(2)} - \bar{x})(\bar{x}_{(2)} - \bar{x})']k}{\sum_i k'(\bar{x}_{i(1)} - \bar{x}_{(1)})(\bar{x}_{i(1)} - \bar{x}_{(1)})'k + \sum_i k'(\bar{x}_{i(2)} - \bar{x}_{(2)})(\bar{x}_{i(2)} - \bar{x}_{(2)})'k}$$

Differentiating with respect to k, setting the result equal to zero, and simplifying we see that we can choose k as follows.

$$k \propto C_W^{-1} \,|\, \bar{x}_{(1)} - \bar{x}_{(2)} \,|$$

where C_W is the pooled within-group covariance matrix (Lattin *et al*, 2003: 436-7).

Clearly, the variables for which there is the greatest difference in means between groups contribute most significantly to this quantity. We may choose to use all p variables from our dataset, in which case k will be a $1 \times p$ vector of coefficients. In that case, all variable differences between groups, regardless of degree, would be used for discrimination. However, if our goal is to reduce the number of variables required for classification, we extract only those variables for which the differences among groups are substantial. We do this through F-tests on the differences between means across groups.

Our first step is to test if there is any significant difference between the groups as a whole. If there is no significant difference, no variable or group of variables will be sufficient to discriminate. We perform an F-test with the Hotelling's T^2 test statistic for this purpose where

$$T^2 = \frac{n_1 n_2}{n_1 + n_2}(\bar{x}_{(2)} - \bar{x}_{(1)})' C_W^{-1} (\bar{x}_{(2)} - \bar{x}_{(1)})$$

and

$$\frac{(n_1 + n_2 - p - 1)}{p(n_1 + n_2 - 2)} T^2 \sim F(p, n_1 + n_2 - p - 1).$$

(Lattin *et al*, 2003: 446). The null hypothesis is that there is no difference among groups. We reject the null in favor of the alternative that there is a significant difference if the T^2 value exceeds the critical F value.

For the three group problem we use Rao's F-Test for Wilks' Λ. Wilks' Λ is defined as

$$\Lambda = \frac{|S_E|}{|S_T|}$$

where $|S_E|$ is the determinant of the residual error sum of squares matrix after accounting for the variance explained by the independent variables, and $|S_T|$ is the determinant of the total sum of squares matrix (Lattin *et al*, 2003: 333). We calculate Rao's test statistic

$$Ra = \left[\frac{1-\Lambda^{1/s}}{\Lambda^{1/s}}\right] \times \left[\frac{\left(1 - ts - \frac{pq}{2}\right)}{pq}\right]$$

where

$$t = (n-1) - \frac{(p+q+1)}{2}$$

$$s = \sqrt{\frac{(p^2q^2-4)}{(p^2+q^2-5)}}$$

n = the number of observations

p = the number of X variables

q = the number of groups -1

Ra follows an F-distribution with pq and $1 + ts - \frac{1}{2}pq$ degrees of freedom (Lattin *et al*, 2003: 335).

Once we have determined that there is a difference among groups, we can test for differences with respect to individual variables. Our test statistic is computed in a similar fashion, but we use only one variable at a time to calculate the differences. This has the effect of determining if any individual variables are useful to discriminate among groups given the other variables in the model (Lattin *et al*, 2003: 446).

These tests of the significance of individual variables provide the basis for our Full Model variable selection. Using the computed *F* statistics, we ranked the variables in descending order. We then attempted to classify countries using progressively more variables until the resulting accuracy no longer showed substantial improvement, and built discriminant functions based on the resulting set of variables.

3.3.2.2. Stepwise Variable Selection in Discriminant Analysis

The mechanics involved in using the Stepwise approach to building the discriminant model are identical to those described above, except that in this case, rather than using all available variables in the initial model, we apply an iterative approach to construct the model one variable at a time. To do this, the individual F-tests are completed on each variable and the most significant is added to the model. The second most significant variable is then added, and so on. At each step, the significance of each variable in the new model is tested as described above for the full model. Any variable which no longer significantly contributes to the model is removed.

The method just described is called forward stepwise selection because we start with an empty model and add variables until no improvement is realized. Conversely, backward selection involves starting with all variables in the initial model, and removes variables one at a time until the resulting model no longer provides sufficient accuracy, retesting for significance of individual variables remaining in the model at each step. We employed both of these methods, along with the full model selection, for comparison's sake. As expected, these three methods provided similar lists of key variables.

3.3.2.3. Three Group Discriminant Analysis

The extension of the two-group discriminant problem to three groups is fairly straight forward. The solution is to add a second discriminant function perpendicular to the first which can further discriminate among groups. This can be seen more easily with sample plots.

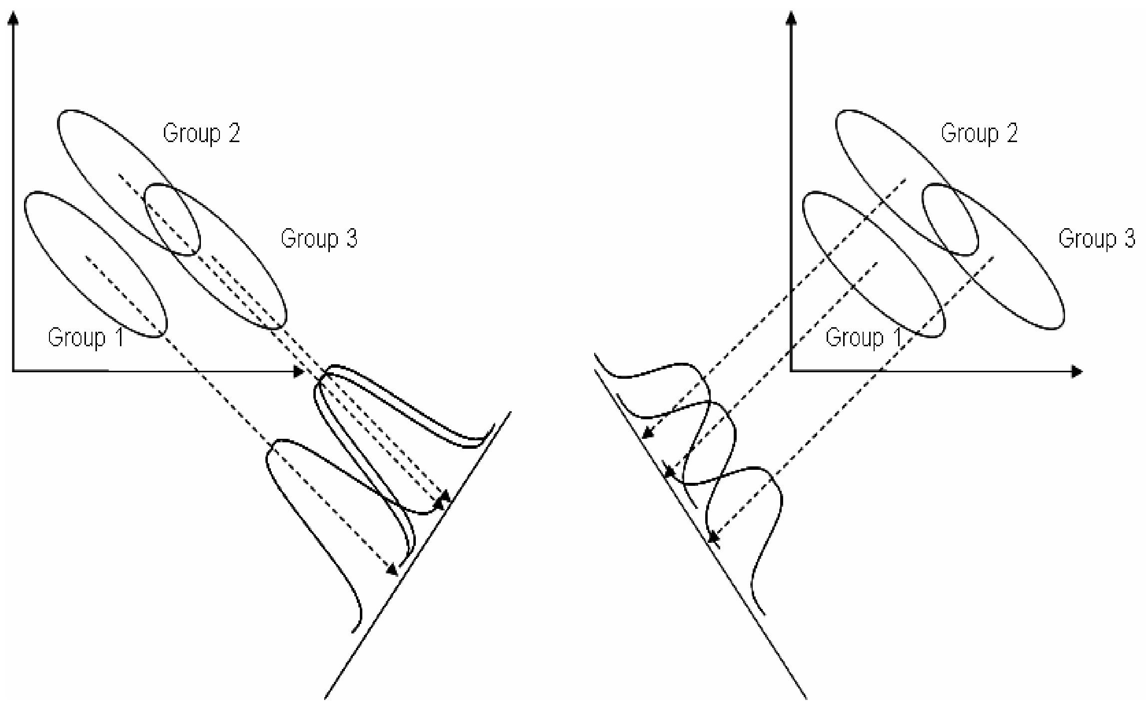

Figure 3-5: Multiple Discriminant Functions for the Three Group Problem
(Lattin *et al*, 2003: 457-8)

Here we see that the first discriminant function provides separation between Group 1 and the other two, while the second is needed to distinguish Group 2 from Group 3. Therefore, our DA resulted in two mutually orthogonal discriminant functions.

3.3.3. Summary of Variable Selection Procedures

The methods described in the preceding sections were used to achieve the first primary goal of this effort – to identify a relatively small subset of variables that can be used to successfully discriminate between stable and unstable states. The next section builds on these results by developing discriminant functions for classifying states based on these variables.

3.4. Classifying States

Recall that in order to use DA to classify observations into groups, we must begin with a hypothesized, *a priori* classification. For the initial Discriminant Analysis in this study, Thomas Barnett's identification of Core, Rim, and Gap states served as a proxy for ground truth as no official governmental classification of failing states was available at the open source level. We first tested this classification to see if there truly do appear to be differences among groups. Next, we performed several Discriminant Analyses using the attributes chosen through the variable selection techniques described earlier. Following an extensive look at the Barnett classifications, we compare results with the Fund for Peace 2006 Failed State Index using the same variables. The variables used and the results of the DA can be found in Chapter 4.

3.5. Chapter Summary

This chapter outlines the various methods we employed to achieve the two primary objectives of this study. First, it describes the techniques we used to select the variables most important for the purpose of assessing state stability. Second, it provides the mechanics of Discriminant Analysis which we used to classify states in terms of their overall stability. Chapter 4 provides the results of these analyses.

4. Analysis Results

4.1. Introduction

This chapter contains the results of the variable selection and Discriminant Analysis described in Chapter 3. Significant conclusions and recommendations for future study are outlined in Chapter 5.

4.2. Variable Selection

We used several methods to identify the key variables most useful in classifying states as stable, borderline, or unstable. The results of each method are presented here.

4.2.1. Exploratory Factor Analysis

As described in the Methodology section of this paper, Factor Analysis (FA) was used to reduce the dimensionality of our final dataset by uncovering its underlying structure. A key product of FA is a matrix of factor scores as shown in Table 4-1. Columns represent the common factors, and rows represent each of the variables in our dataset.

Table 4-1: Factor Loadings Matrix Before Rotation

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Log(A100)	-0.292	**0.802**	-0.259	-0.126	-0.131	0.208	0.016	-0.118	-0.011	0.019
A110	0.377	-0.225	0.055	0.005	0.061	0.140	0.138	-0.167	0.079	-0.069
A113	0.230	0.032	-0.213	-0.062	0.021	0.301	0.143	0.110	0.033	-0.173
A114	0.336	-0.140	0.024	-0.221	-0.298	0.152	-0.175	-0.033	-0.065	0.081
A116	-0.437	0.218	-0.295	-0.033	-0.288	0.133	0.124	0.147	0.273	-0.043
Log(A118)	-0.172	**0.541**	-0.117	0.073	-0.068	-0.084	0.084	0.072	0.491	0.037
Log(A119)	**0.902**	0.085	0.046	0.203	0.058	0.038	0.017	0.079	0.032	0.043
A120	**-0.608**	0.148	-0.320	-0.069	-0.190	0.043	0.021	0.149	0.071	-0.097
A122	**-0.549**	0.017	-0.439	0.153	-0.058	-0.191	0.080	-0.071	-0.078	0.042
A124	-0.146	0.136	0.134	-0.235	-0.102	0.063	0.013	-0.160	0.089	-0.186
Log(A126)	-0.046	**-0.512**	0.327	-0.202	-0.031	-0.082	0.029	0.008	0.148	0.117
Log(A130)	-0.307	0.178	-0.155	-0.200	0.096	-0.185	-0.176	0.023	-0.048	-0.303
Log(A133)	0.446	-0.157	-0.451	0.111	0.266	-0.073	0.163	0.009	0.005	0.007
A135	0.321	-0.055	-0.074	0.289	0.093	-0.443	0.082	-0.158	-0.084	-0.141
Log(A136+0.001)	0.004	-0.091	-0.187	0.061	-0.229	-0.135	-0.031	0.132	-0.232	0.013
A141	-0.390	**-0.518**	0.021	-0.040	0.073	0.004	0.024	0.060	0.191	0.107
Log(A144)	0.044	0.203	-0.200	-0.005	-0.156	**-0.557**	-0.082	0.185	0.000	-0.068
Log(A152)	-0.464	0.147	-0.445	-0.049	0.267	-0.108	-0.214	-0.057	0.069	-0.231
Log(A153)	-0.052	-0.304	0.096	-0.059	0.070	0.230	-0.316	0.229	0.073	0.199
Log(A155)	-0.346	**0.705**	-0.297	-0.125	0.281	0.119	-0.077	0.007	0.016	0.283
Log(A159+0.001)	0.066	-0.139	-0.118	0.213	-0.188	-0.139	0.379	-0.106	0.113	0.404
Log(A160+0.001)	0.204	-0.067	-0.288	0.072	-0.195	-0.090	0.204	-0.034	0.046	0.144
Log(A166)	0.206	-0.133	0.146	0.075	**-0.638**	0.106	0.154	-0.105	-0.015	-0.415
Log(A167+0.001)	**-0.532**	-0.187	-0.180	0.395	0.194	0.226	0.059	0.099	-0.173	0.001
Log(A172+0.001)	0.012	0.433	0.409	-0.311	0.048	-0.193	0.302	0.259	-0.238	-0.012
Log(A174)	**-0.871**	-0.018	0.142	-0.014	0.103	0.023	0.101	-0.067	-0.103	0.064
A175	**0.630**	-0.249	-0.195	0.044	0.002	-0.024	-0.144	-0.055	-0.129	-0.040
A177	**0.575**	-0.014	-0.088	-0.245	0.136	-0.071	-0.063	-0.199	-0.109	-0.045
Log(A180)	-0.270	-0.137	-0.024	0.388	0.050	0.037	-0.027	0.179	-0.068	-0.025
Log(A181)	0.205	-0.257	0.105	-0.075	0.004	-0.040	-0.040	0.013	-0.044	-0.082
Log(A182)	0.389	0.422	0.135	0.038	0.195	0.219	0.066	0.173	0.111	-0.157
Log(A184)	0.208	-0.317	-0.193	-0.412	-0.020	-0.110	-0.058	0.173	0.138	0.063
A185	**0.688**	0.186	-0.085	0.174	0.080	0.021	-0.066	0.205	-0.108	0.083
A186	0.167	0.247	-0.063	-0.059	0.309	0.233	-0.261	0.262	-0.110	-0.036
A190	**-0.886**	0.021	0.186	0.170	0.095	-0.095	0.018	0.087	0.072	-0.064
A192	**0.604**	0.086	-0.148	-0.053	-0.183	-0.121	-0.195	-0.105	-0.081	0.073
Log(A193)	**-0.819**	-0.149	0.047	-0.091	0.006	-0.119	0.028	0.020	-0.040	-0.021
Log(A209)	0.005	0.415	0.088	0.046	0.120	-0.101	0.105	-0.205	-0.059	0.134
A211	-0.007	-0.190	-0.058	-0.209	-0.319	0.081	-0.103	0.088	-0.201	0.083
Log(A215)	**-0.832**	0.025	0.002	-0.051	0.084	-0.175	0.079	-0.082	-0.072	-0.102
Log(A216)	-0.459	0.145	0.074	0.256	-0.001	-0.282	-0.342	-0.096	0.150	0.021
Log(A221+0.001)	-0.023	**0.657**	0.332	-0.286	-0.029	-0.109	0.317	0.254	-0.251	0.034
A225	0.332	0.205	0.336	-0.232	0.118	-0.304	-0.056	0.063	0.151	0.037
Log(A231+0.001)	**0.877**	0.088	-0.264	0.054	0.001	-0.103	-0.048	-0.053	0.033	0.033
A236	-0.124	0.086	-0.131	0.016	-0.164	0.130	0.109	0.098	-0.016	0.010
A239	-0.236	0.087	-0.234	-0.133	0.023	-0.059	0.105	0.081	-0.114	0.093
Log(-A243)	**0.532**	**0.671**	-0.126	0.157	-0.191	0.159	0.050	-0.068	-0.018	-0.036
A244	-0.008	-0.049	-0.053	0.054	-0.005	-0.100	-0.075	-0.036	-0.128	-0.019
Log(A246+0.001)	**0.541**	-0.177	-0.146	0.032	0.054	0.035	0.051	0.127	0.172	-0.138
A247	-0.151	0.172	-0.170	0.081	-0.063	-0.240	-0.087	0.320	0.043	-0.029
Log(A248)	-0.147	0.495	0.016	0.020	-0.276	0.042	-0.256	-0.158	-0.121	0.141
A250	0.120	0.217	-0.025	**0.560**	0.037	0.113	-0.016	0.025	-0.173	-0.078
A252	-0.281	0.470	-0.022	-0.288	0.089	0.138	-0.055	-0.351	0.098	-0.027
A253	**-0.707**	-0.312	0.042	0.013	0.254	0.170	0.111	-0.079	-0.062	-0.024
A257	**-0.603**	-0.272	-0.349	-0.325	0.125	0.010	0.040	-0.182	-0.165	-0.034
A259	**0.552**	-0.140	-0.368	-0.366	-0.020	-0.017	-0.125	-0.018	-0.070	0.102
Log(A262)	0.486	0.276	0.484	0.101	0.158	-0.081	-0.204	-0.086	0.085	-0.042
Log(A263)	0.449	-0.255	-0.265	-0.306	0.180	0.034	0.255	0.104	0.008	-0.096
Log(A264)	**0.701**	0.043	-0.138	-0.077	0.329	-0.086	0.225	-0.047	0.099	-0.117
Log(A266+0.001)	0.398	0.135	0.024	0.067	0.214	-0.007	0.204	-0.223	-0.068	0.068

Shown are the factor scores for each variable on the first ten principal factors. Loadings higher than 0.5 are highlighted in bold type. Again, in the interest of space, 3-digit codes have been used in place of series descriptions. Complete variable names are provided in Appendix B. Where log(AXXX) is shown, this indicates the variable was transformed using the natural logarithm. Log(AXXX + 0.001) indicates that an epsilon value was added to allow us to take the natural log of variables which contained zeroes.

Note that with *p* independent variables, as many as *p* principal factors are possible. Our decision to retain only the first ten factors was aided by the eigenvalues corresponding to each factor, and a Scree Plot showing the amount of variation in the dataset explained by additional factors.

Table 4-2: Eigenvalues and Variance Accounted for Before Rotation

	Eigenvalue	Variability (%)	Cumulative %
F1	12.321	20.535	20.535
F2	5.274	8.790	29.326
F3	2.798	4.663	33.989
F4	2.231	3.719	37.707
F5	1.899	3.165	40.873
F6	1.619	2.698	43.570
F7	1.376	2.293	45.863
F8	1.183	1.971	47.834
F9	1.027	1.712	49.547
F10	0.964	1.607	51.153
F11	0.785	1.308	52.462
F12	0.688	1.147	53.609
F13	0.591	0.986	54.594
F14	0.539	0.899	55.493
F15	0.492	0.820	56.313
F16	0.447	0.744	57.058
F17	0.396	0.660	57.718
F18	0.364	0.607	58.325
F19	0.362	0.603	58.928
F20	0.299	0.498	59.427
F21	0.253	0.422	59.848
F22	0.234	0.390	60.238
F23	0.211	0.352	60.591
F24	0.156	0.261	60.851
F25	0.153	0.254	61.106
F26	0.114	0.189	61.295
F27	0.094	0.157	61.453
F28	0.064	0.107	61.560
F29	0.029	0.049	61.609
F30	0.007	0.012	61.621

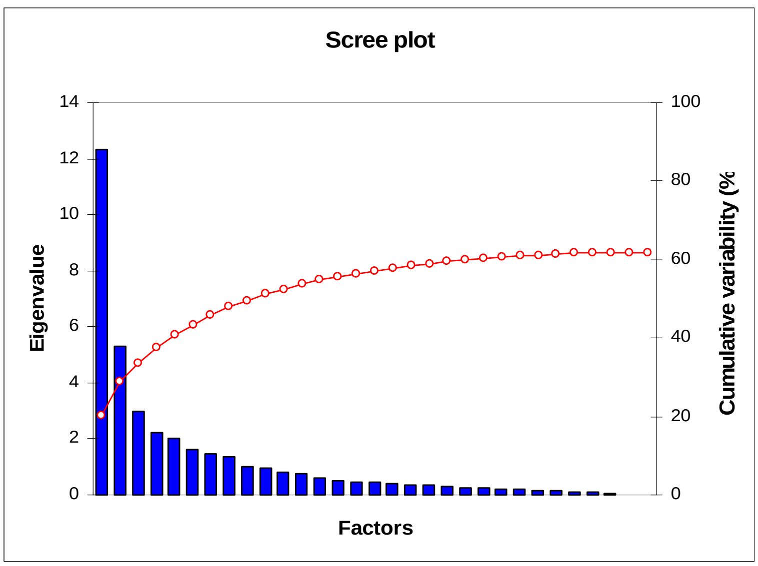

Figure 4-1: Plot of Eigenvalues and Explained Variance

After the first two principal factors, there appears to be relatively little increase in the amount of variability explained by adding additional factors to the model, and almost no improvement after the first ten factors are included. The first two factors account for approximately 30% of the total variation in the data, whereas Factors 11 through 30 account for only 9%. This suggests that we capture a large portion of the total variation available in the dataset with the first few factors, which is typical in FA.

To aid in factor characterization and variable selection, we next performed a Varimax rotation. We retained those factors with eigenvalues greater than or equal to 1.0, meaning the first ten factors were retained, rounding the tenth value of 0.964 to 1.0. The resulting eigenvalues and factor scores are shown here.

Table 4-3: Variance Accounted for After Varimax Rotation

	Variability (%)	Cumulative %
D1	19.575	19.575
D2	7.605	27.180
D3	4.335	31.515
D4	3.215	34.730
D5	2.704	37.435
D6	3.110	40.545
D7	3.711	44.256
D8	2.514	46.770
D9	2.151	48.921
D10	2.232	51.153

Note that the amount of variation explained by each factor may have changed, but the overall variation explained by the first ten rotated factors remains the same at 51%. We have not changed the structure of the data, only its orientation so that we may better understand it.

Table 4-4: Factor Loadings After Varimax Rotation

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Log(A100)	-0.118	**0.914**	0.173	0.018	-0.042	0.024	-0.026	-0.023	0.027	0.030
A110	0.302	-0.218	-0.112	-0.054	-0.104	-0.275	0.133	0.134	0.016	-0.032
A113	0.236	0.110	-0.042	0.101	-0.112	-0.124	0.355	-0.077	0.077	0.111
A114	0.317	-0.076	-0.062	-0.226	-0.196	-0.085	-0.016	-0.274	-0.233	-0.002
A116	-0.337	0.423	-0.085	0.002	-0.189	0.168	0.162	-0.231	0.291	-0.115
Log(A118)	-0.040	0.496	0.069	-0.066	0.037	0.165	-0.108	0.018	**0.546**	-0.111
Log(A119)	**0.899**	-0.159	0.063	0.137	0.022	-0.096	-0.026	0.057	0.081	-0.030
A120	**-0.522**	0.372	-0.084	0.040	-0.104	0.267	0.164	-0.186	0.102	0.010
A122	-0.482	0.257	-0.225	0.148	0.049	0.356	0.119	0.113	-0.079	-0.209
A124	-0.158	0.159	0.098	-0.233	-0.207	-0.113	-0.032	0.057	0.044	0.141
Log(A126)	-0.174	**-0.524**	-0.015	-0.318	-0.011	-0.152	-0.025	-0.118	0.024	-0.104
Log(A130)	-0.273	0.207	0.031	-0.112	0.027	0.292	0.058	0.116	-0.027	0.353
Log(A133)	0.435	-0.096	-0.230	0.124	0.206	0.107	0.406	0.217	-0.007	-0.099
A135	0.288	-0.214	-0.045	0.117	-0.007	0.274	-0.064	0.476	-0.031	-0.085
Log(A136+0.001)	0.018	-0.049	-0.024	0.115	-0.111	0.301	0.057	-0.114	-0.213	-0.096
A141	-0.461	-0.350	-0.257	-0.111	0.106	-0.055	0.110	-0.142	0.097	-0.109
Log(A144)	0.100	0.064	0.130	-0.085	0.008	**0.641**	-0.061	0.090	0.049	-0.028
Log(A152)	-0.382	0.349	-0.279	-0.005	0.216	0.297	0.148	0.172	0.042	0.306
Log(A153)	-0.060	-0.234	-0.181	-0.036	0.207	-0.136	-0.065	-0.436	-0.016	0.119
Log(A155)	-0.172	**0.789**	0.135	0.033	0.472	0.026	-0.001	-0.040	0.048	0.028
Log(A159+0.001)	0.057	-0.072	-0.077	0.034	-0.003	0.021	0.046	0.058	0.063	**-0.666**
Log(A160+0.001)	0.217	0.026	-0.120	-0.002	-0.086	0.145	0.177	0.020	-0.011	-0.352
Log(A166)	0.151	-0.128	-0.005	0.008	**-0.819**	-0.016	-0.021	-0.021	-0.005	-0.027
Log(A167+0.001)	**-0.509**	-0.001	-0.251	**0.530**	0.134	-0.048	0.108	-0.042	-0.034	-0.021
Log(A172+0.001)	-0.020	0.067	**0.832**	-0.063	0.028	0.021	-0.004	0.040	0.010	0.048
Log(A174)	**-0.878**	0.106	0.076	0.074	0.100	-0.082	-0.073	0.018	-0.041	-0.047
A175	**0.596**	-0.244	-0.228	0.001	-0.022	0.054	0.116	0.047	-0.233	0.048
A177	**0.532**	-0.060	0.006	-0.244	0.062	-0.056	0.132	0.202	-0.234	0.118
Log(A180)	-0.251	-0.122	-0.138	0.406	0.042	0.086	-0.065	-0.067	0.069	-0.010
Log(A181)	0.134	-0.302	-0.019	-0.089	-0.061	-0.033	0.040	0.000	-0.082	0.080
Log(A182)	0.430	0.190	0.277	0.154	0.040	-0.197	0.020	0.024	0.288	0.246
Log(A184)	0.157	-0.230	-0.090	-0.396	0.090	0.154	0.318	-0.209	-0.028	0.016
A185	**0.731**	-0.014	0.100	0.222	0.132	0.057	0.005	-0.048	-0.018	0.026
A186	0.230	0.170	0.087	0.162	0.297	-0.059	0.052	-0.181	-0.020	0.392
A190	**-0.869**	0.042	0.045	0.168	0.076	0.084	-0.196	0.018	0.213	0.042
A192	**0.632**	0.038	-0.061	-0.150	-0.064	0.149	-0.078	0.007	-0.213	-0.034
Log(A193)	**-0.838**	-0.009	-0.001	-0.042	0.034	0.120	-0.007	-0.033	-0.023	-0.004
Log(A209)	0.050	0.299	0.231	0.017	0.137	-0.066	-0.180	0.261	-0.008	-0.111
A211	-0.022	-0.067	-0.018	-0.115	-0.175	0.070	0.070	-0.326	-0.299	-0.047
Log(A215)	**-0.831**	0.138	0.047	0.002	0.045	0.146	-0.014	0.156	-0.014	0.031
Log(A216)	-0.380	0.121	-0.162	0.019	0.118	0.264	-0.484	0.089	0.132	0.056
Log(A221+0.001)	0.001	0.316	**0.874**	-0.002	0.001	0.024	-0.027	-0.007	0.019	0.006
A225	0.305	-0.115	0.369	-0.326	0.148	0.045	-0.198	0.102	0.159	0.098
Log(A231+0.001)	**0.899**	-0.009	-0.098	-0.047	0.030	0.112	0.098	0.135	-0.044	-0.055
A236	-0.086	0.172	0.015	0.103	-0.119	0.033	0.114	-0.145	0.026	-0.090
A239	-0.206	0.186	0.068	-0.001	0.118	0.158	0.201	-0.040	-0.096	-0.088
Log(-A243)	**0.657**	**0.542**	0.180	0.177	-0.185	-0.021	-0.100	0.070	0.069	-0.028
A244	-0.009	-0.042	-0.049	0.045	0.008	0.111	-0.038	0.058	-0.135	0.016
Log(A246+0.001)	**0.508**	-0.221	-0.136	0.000	-0.044	0.010	0.244	0.010	0.163	0.060
A247	-0.076	0.106	0.068	0.104	0.077	0.433	-0.015	-0.115	0.150	0.034
Log(A248)	-0.023	**0.511**	0.085	-0.012	-0.083	0.068	-0.390	-0.104	-0.165	-0.017
A250	0.189	0.116	-0.046	**0.569**	-0.040	-0.001	-0.190	0.117	0.023	0.011
A252	-0.213	**0.579**	0.068	-0.269	0.046	-0.192	-0.077	0.158	0.001	0.143
A253	**-0.764**	-0.103	-0.150	0.117	0.127	-0.218	0.133	0.037	-0.042	0.035
A257	**-0.637**	0.095	-0.230	-0.178	0.102	0.054	0.366	0.058	-0.305	0.034
A259	**0.540**	-0.024	-0.145	-0.317	0.091	0.103	0.320	-0.103	-0.282	0.016
Log(A262)	0.480	-0.094	0.247	-0.051	0.071	-0.185	-0.457	0.176	0.136	0.216
Log(A263)	0.366	-0.206	-0.003	-0.158	0.055	-0.037	**0.582**	0.053	-0.031	0.027
Log(A264)	**0.653**	-0.103	0.070	-0.073	0.141	-0.072	0.321	0.343	0.120	0.051
Log(A266+0.001)	0.375	0.030	0.103	0.046	0.107	-0.202	0.043	0.324	-0.047	-0.111

Again, loadings above 0.5 are highlighted. One of the key differences between these scores and the scores before rotation is that now there is at least one variable significantly loaded on each of the retained factors, with the exception of Factor 8. Before rotation, no variables loaded heavily on factors 7 through 10. Another preliminary finding is that many variables, 18 of the 60, load quite heavily on the first principal factor. This suggests that the first factor may be an umbrella encompassing many attributes across the spectrum of national stability.

Table 4-5 provides a list of the variables with loadings above 0.5 on each of the factors, as well as suggested labels for each. For Factor 8, for which no variables loaded above 0.5, the variables listed had loadings of 0.48 and -0.44 respectively. Variables in bold loaded negatively on the given factor.

Table 4-5: Characterization of Principal Factors

Factor 1: The Big Picture - This factor encompasses the vast majority of variables experts use in determining the overall status of a country, and determining national stability.	
Log(A231+0.001)	Carbon dioxide emissions (CO2), metric tons of CO2 per capita (CDIAC)
Log(A119)	GDP Per Capita
A185	Urban population (% of total)
Log(-A243)	Balance of Payments: imports of goods, free on board, US$ (IMF)
Log(A264)	Number of Recorded Drug Crimes Per 1000 Pop
A192	Children 1 year old immunized against measles, percentage
A175	Ratio of female to male enrollments in tertiary education
A259	Enrolment in total secondary. Public and private. All programs. Total %
A177	Ratio of girls to boys in primary and secondary education (%)
Log(A246+0.001)	Exchange rate, US$ per national currency (IMF)
Log(A167+0.001)	Population growth (annual %)
A120	Political Terror Rating
A257	School age population. Tertiary. Total %
A253	School age population. Primary. Total %
Log(A215)	Tuberculosis death rate per 100,000 population
Log(A193)	Population undernourished, percentage
A190	Children under five mortality rate per 1,000 live births
Log(A174)	Pupil-teacher ratio, primary
Factor 2: Sustainability - This factor seems to capture a country's population and their ability to provide for it. Also included is the Count of Entries, which measures various organizations' ability/desire to collect data on each nation.	
Log(A100)	Population
Log(A155)	Land area (sq. km)
A252	Count of entries in database
Log(-A243)	Balance of Payments: imports of goods, free on board, US$ (IMF)
Log(A248)	Imports of goods and services, current prices
Log(A126)	Aid per capita (current US$)
Factor 3: Women's Rights	
Log(A221+0.001)	Seats held by women in national parliament
Log(A172+0.001)	Proportion of seats held by women in national parliament (%)
Factor 4: Population Growth	
A250	Migration, international net rate per year
Log(A167+0.001)	Population growth (annual %)
Factor 5: Crowdedness	
Log(A166)	Population density (people per sq. km)
Factor 6: Economic Growth	
Log(A144)	GDP per capita growth (annual %)
Factor 7: Crime Rate	
Log(A263)	Number of Recorded Murders Attempted Per 1000 Pop
Factor 8: Openness	
A135	Exports of goods and services (% of GDP)
Log(A153)	International tourism, expenditures (% of total imports)
Factor 9: Displaced Persons	
Log(A118)	Refugees
Factor 10: Military Focus	
Log(A159+0.001)	Military expenditure (% of GDP)

The insights gained from the characterization of the principal factors suggested two methods for selecting variables for constructing a discriminant model. The first was to select the variable most heavily loaded on each of the ten factors listed above, starting with the Big Picture factor. Although our hypothesis was that successful discrimination was possible with no more than ten variables, we continued by selecting the second most important variables from each factor to see if additional variables added to the model. Our second method was to focus on the two factors which explained the majority of the variation in the data, Big Picture and Sustainability. We chose variables in order of factor loading on the Big Picture factor until all loadings greater than 0.5 were exhausted, then moved on to Sustainability. Table 4-6 provides the variables chosen using both approaches. The results of the DA are provided in Section 4.3.

Table 4-6: Variable Selection from Factor Analysis

Selecting Variables from All Factors	Selecting Variables from Factors 1 and 2
Carbon dioxide emissions , metric tons of CO2 per capita	Carbon dioxide emissions, metric tons of CO2 per capita
Population	GDP Per Capita
Proportion of seats held by women in national parliament	Children under five mortality rate per 1,000 live births
Number of Recorded Crimes Per 1000 Pop	Pupil-teacher ratio, primary
Migration, international net rate per year	Population undernourished, percentage
GDP per capita growth (annual %)	Tuberculosis death rate per 100,000 population
Imports of goods and services, current prices	School age population. Primary. Total %
Population density (people per sq. km)	Urban population (% of total)
Military expenditure (% of GDP)	Number of Recorded Drug Crimes Per 1000 Pop
GDP Per Capita	Balance of Payments: imports of goods, free on board, US$ (IMF)
Land area (sq. km)	Children 1 year old immunized against measles, percentage
Seats held by women in national parliament	Ratio of female to male enrollments in tertiary education
School age population. Tertiary. Total %	School age population. Tertiary. Total %
Population growth (annual %)	Enrolment in total secondary. Public and private. All programs. Total %
GDP annual growth rate, 1990 prices, US$	Ratio of girls to boys in primary and secondary education (%)
Children under five mortality rate per 1,000 live births	Political Terror
Refugees	Population growth (annual %)
Pupil-teacher ratio, primary	Exchange rate, US$ per national currency (IMF)
Count of entries	Population
Population undernourished, percentage	Land area (sq. km)

4.2.2. Variable Selection via Discriminant Analysis

As described in Chapter 3, variable selection within DA was accomplished in two ways; Stepwise Forward Selection, and Significance within the Full Model. The resulting prioritization of variables is shown below.

Table 4-7: Variable Selection from Discriminant Analysis

Forward Stepwise Selection	Full Model Selection
Balance of Payments: imports of goods, free on board, US$ (IMF)	Balance of Payments: imports of goods, free on board, US$ (IMF)
Population undernourished, percentage	Population
Aid per capita (current US$)	Population undernourished, percentage
Political Terror	Aid per capita (current US$)
School age population. Tertiary. Total %	Political Terror
Children under five mortality rate per 1,000 live births	GDP Per Capita
Land area (sq. km)	Children under five mortality rate per 1,000 live births
Tuberculosis death rate per 100,000 population	Land area (sq. km)
School age population. Primary. Total %	School age population. Tertiary. Total %
Political Rights	Tuberculosis death rate per 100,000 population
Share of women in wage employment in the non-agricultural sector	Pupil-teacher ratio, primary
Agricultural production index, 1999-2001=100	Carbon dioxide emissions (CO2), metric tons of CO2 per capita (CDIAC)
Enrolment in total secondary. Public and private. All programs. Total %	School age population. Primary. Total %
Inflation, GDP deflator (annual %)	Political Rights
Largest Ethnic Group %	Food imports (% of merchandise imports)
GDP per capita growth (annual %)	% time in conflict 1990-2003
Number of Disaster Related Deaths (Zero when empty)	Number of Recorded Crimes Per 1000 Pop
Children 1 year old immunized against measles, percentage	Share of women in wage employment in the non-agricultural sector
Use of IMF credit (DOD, current US$)	Population growth (annual %)
Balance of Payments: trade balance, goods and services, US$ (IMF)	Number of Recorded Drug Crimes Per 1000 Pop

Following variable selection, we performed Discriminant Analysis using Barnett's Core, Rim, Gap Classification with each of the four sets of variables defined above. The results of the DA for each of the models are provided next.

4.3. Discriminant Analysis - Barnett

Our initial classification, based on Thomas Barnett's work, is shown in Table 4-8. He divides the countries of the World into three main categories. While these categories are not specifically defined as stable or failing states, they do provide an open source proxy for the classification. The first category is the "Old Functioning Core" which is made up of nations whose economies are integrated with the rest of the World, and who are actively participating in globalization. The "Non-Integrated Gap" consists of nations largely left out of the global integration process. In between are states which are working to become part of the global economy, but for various reasons may not be considered fully integrated at this time. Several Rim States such as China, Russia, Brazil and India, are further along in that process and make up the "New Core" (Barnett Glossary Online: http://www.thomaspmbarnett.com/glossary.htm).

Table 4-8: Initial Classification

[http://www.thomaspmbarnett.com/glossary.htm]

Integrated Core	New Core and Rim States	Non-Integrated Gap
North America	China	Caribbean Rim
Europe	Russia	Andean South America
Japan	Argentina	Africa (except South Africa)
Industrialized Asia	Brazil	Portions of the Balkans
Australia	Chile	Caucasus
New Zealand	Mexico	Central Asia
	South Africa	Middle East
	Morocco	Southeast Asia
	Algeria	
	Greece	
	Turkey	
	Pakistan	
	India	
	Thailand	
	South Korea	
	Malaysia	
	Philippines	
	Indonesia	

We first tested the classification to see if there were statistically significant differences among groups, based on our data. For this we computed Rao's F-Test for Wilks' Λ, and obtained the following results:

Wilks' Lambda test (Rao's approximation):	
Lambda	0.073
F (Observed value)	6.189
F (Critical value)	1.281
DF1	120
DF2	276
p-value	< 0.0001
alpha	0.05

Test interpretation:
H0: The means vectors of the 3 classes are equal.
Ha: At least one of the means vector is different from another.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

This suggests that there *are* differences among the groups, and therefore we may be able to discriminate countries based on our initial classification.

We next built multiple Discriminant Functions, based on the four sets of variables selected earlier. For comparison's sake, we also discriminated based on the Factor Scores produced during FA, and the Component Scores from Principal Component Analysis (PCA). While we did not use PCA in this study, the results are provided here as it is a common data reduction technique readers may be familiar with, and it is readily available in most software packages. Adding it to the analysis required very little coding or computation time. Refer to Lattin *et al*, 2003 or Dillon *et al*, 1984 for details on PCA. Recall that in order to recreate the FA and PCA scores, an analyst would need all 60 variables used during the analysis. For this reason, discriminating based on Factor or

Component Scores is less desirable from a data collection efficiency point-of-view, but may be useful for comparison as more data is included.

Considering our goal of determining a minimal set of variables required to classify states, discriminant functions were built one variable at a time. At each iteration, we checked the accuracy of the model by its ability to classify states into their prior classes. A confusion matrix shows the number and percentage of countries classified into each group as compared to their *a priori* designation. Table 4-9 is the confusion matrix for one such iteration. In this case, all variables in the dataset were used to construct a discriminant function.

Table 4-9: Confusion Matrix Using All Variables

from \ to	Core	Rim	Gap	Total	% correct
Core	50	0	1	51	98.04%
Rim	0	19	0	19	100.00%
Gap	11	7	112	130	86.15%
Total	61	26	113	200	90.50%

Here we see an overall classification accuracy of 90.50%. This should represent the optimal accuracy we could hope to achieve using any subset of variables since all data available were used to construct this model. It is possible that one or more variables serve to confuse the situation and that we could see better results if those variables were removed; however we should not expect to achieve significantly greater accuracy using less data with the same analysis parameters. Examining the matrix, we notice that the model does exceptionally well at identifying countries Barnett classified as Core or Rim. Of the 70 Core and Rim states, only one, New Caledonia, was misclassified. New Caledonia is a small, French occupied island in the Pacific Ocean off the East coast of Australia (http://en.wikipedia.org/wiki/New_Caledonia, Feb 2007), and was one of 13 countries we retained for our study for which we found less the half of the data. This means that due to the data imputation, the data used to classify New Caledonia came more from other countries than from the nation itself. Interestingly, as seen later in Table 4-16, the reduced model using only ten variables classifies this country correctly, though only five of the ten variables were populated.

The model does not perform as strongly when identifying Gap states, though accuracy is still over 86%. The overall accuracies for each variable selection method as progressively more variables are added to the model are plotted in Figure 4-2.

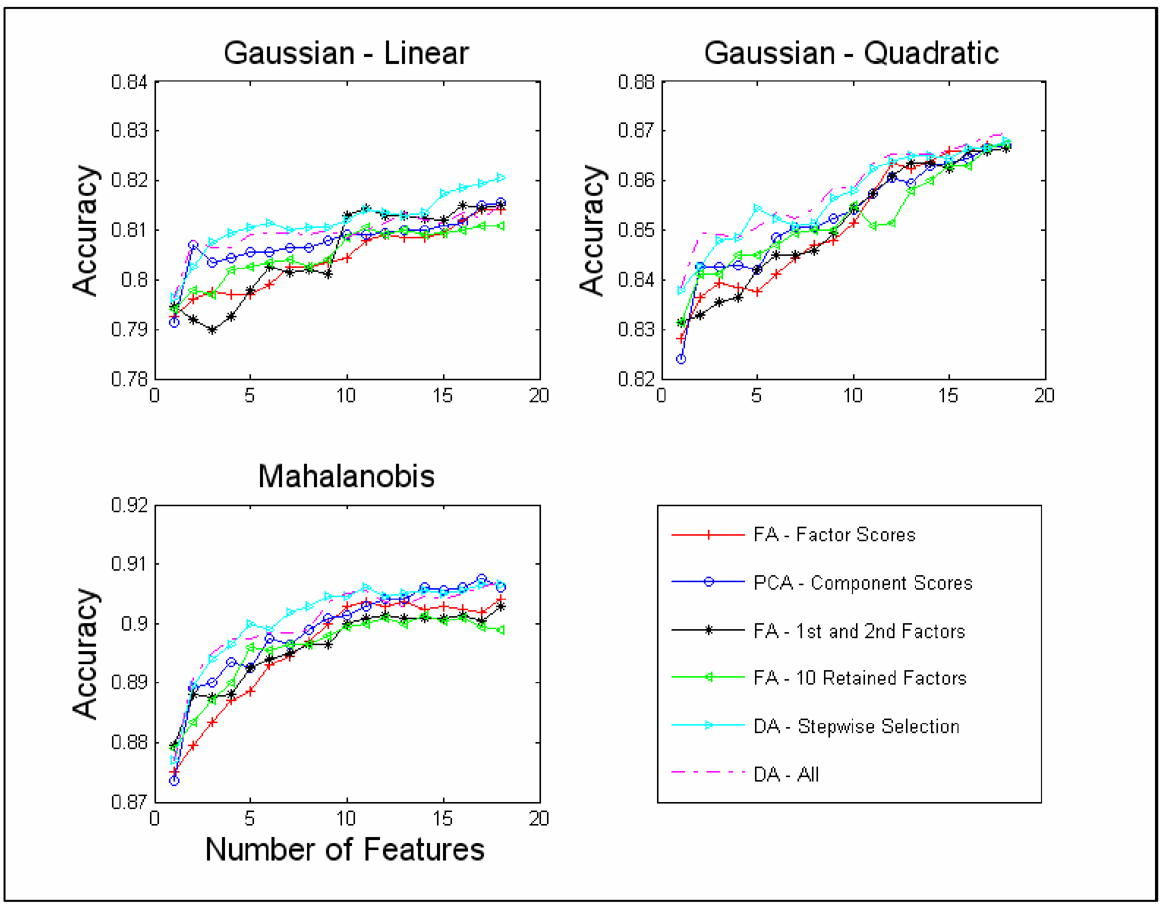

Figure 4-2: Model Accuracy

The three plots show the accuracies of the models as additional features are added based on the Linear Discriminant Function used in this thesis, as well as two other methods which are included for comparison. Several key insights can be gleaned from these figures. First, regardless of the discriminant function used, the ranking of the variable selection procedures remains fairly constant, with Stepwise and Full Model DA selection performing slightly better than the others. Simply put, this means that the variables selected using those methods perform better for discriminating states, though only by approximately 1%. The similarity in performance is not surprising considering the overlap in the lists of variables used to construct each model.

Second, the marginal improvement in accuracy with each additional variable diminishes as the model grows, which is to be expected, particularly if we use Mahalanobis' Method for building the discriminant functions. For example, if we look at the Mahalanobis chart in the lower left corner, we see that both DA methods start out with approximately 87.5% accuracy using only one variable, improve to 90% with seven variables, but then appear to level off. The improvement in accuracy as we add variables to the linear function appears more constant. Recall that we could achieve 90.5% accuracy if we used all 60 variables as shown in Table 4-9. Since we are able to achieve this accuracy with fewer than 10 variables using the Mahalanobis Method, this may be a technique worth exploring in future work.

One result we found surprising initially was that the dimension reduction techniques, PCA and FA, did not outperform the techniques involving individual variables. Since the first principal components or first principal factors account for a significant amount of variation in several variables, one might expect the models using the component or factor scores to perform significantly better than those using individual variables, at least when only one or two features are in the model. However, remember that the factors capture any variance in the data, regardless of whether or not it is relevant to the classification. If we reexamine Table 4-4 we see that that several of the key variables load very heavily on the first few principal factors. Therefore, these variables may be sufficient proxies for the underlying factors, and they appear to perform just as well for discriminating states as the factors constructed using all 60 variables. This is the first significant finding of this study, and supports our hypothesis that states can be classified using as few as ten objective, readily available measures.

To select our final model, we compared the accuracies of each of the constructed models. The model based on the variables chosen through Stepwise Selection consistently out-performed the others, particularly when staying within our self-imposed limit of using at most ten key variables. Therefore, the remainder of our results is taken from the 10-variable model constructed using Forward Stepwise Selection. The variables comprising that model are listed in Table 4-10.

Table 4-10: Variables Used in Final Model

Variable Code	Series Name
Log(-A243)	Balance of Payments: imports of goods, free on board, US$ (IMF)
Log(A193)	Population undernourished, percentage
Log(A126)	Aid per capita (current US$)
A120	Political Terror
A190	Children under five mortality rate per 1,000 live births
Log(A155)	Land area (sq. km)
A257	School age population. Tertiary. Total %
Log(A215)	Tuberculosis death rate per 100,000 population
A122	Political Rights
A225	Share of women in wage employment in the non-agricultural sector

If we consider the nations classified as Core, Rim, or Gap states, we are interested in whether or not the average value for each of these variables differs significantly across groups, meaning each variables can significantly contribute to the classification model. The results of the tests for differences between group means for each variable are shown in Table 4-11.

Table 4-11: Tests for Differences Between Group Means

Variable	F	DF1	DF2	p-value
Log(-A243)	62.363	2	197	< 0.0001
Log(A193)	54.681	2	197	< 0.0001
Log(A126)	52.514	2	197	< 0.0001
A120	50.266	2	197	< 0.0001
A190	39.896	2	197	< 0.0001
Log(A155)	39.727	2	197	< 0.0001
A257	37.677	2	197	< 0.0001
Log(A215)	34.235	2	197	< 0.0001
A225	22.759	2	197	< 0.0001
A122	30.078	2	197	< 0.0001

From this we see that in fact each of the ten variables show significant differences across groups. Constructing a discriminant function based on these variables, we obtain the resulting linear discriminant functions provided in Table 4-12.

Table 4-12: Discriminant Functions

	Core	Rim	Gap
Intercept	-319.417	-329.287	-309.575
Log(-A243)	19.071	19.242	18.550
Log(A193)	12.654	12.497	13.871
Log(A126)	6.598	5.610	6.234
A120	-6.750	-5.854	-6.250
A190	0.155	0.125	0.165
Log(A155)	-1.727	-1.300	-1.823
A257	1684.570	1754.207	1688.771
Log(A215)	-6.903	-5.709	-6.951
A225	1.005	0.861	0.984
A122	1.392	1.160	1.782

The magnitude of the coefficients on variable 257 warrants further investigation. Returning to the data, variable 257, Percentage of the Population aged 18-22, is the only variable retained as a percentage, and not transformed via natural logarithm. Furthermore, the maximum value achieved is 12.7% meaning the values are very small in comparison to other variables. The unusually large coefficients therefore do not have as drastic an effect as one might imagine.

To use these functions, we input a country's values for each variable, multiply by the given coefficients, and sum the values together with the Intercept value. For example, if we wish to classify Somalia, we first collect the necessary data.

Table 4-13: Classification Example - Somalia

Log(-A243)	21.504
Log(A193)	3.784
Log(A126)	3.179
A120	4.000
A190	225.000
Log(A155)	13.349
A257	0.092
Log(A215)	4.787
A225	45.400
A122	6.000

Multiplying each of these values by their respective coefficients and summing we obtain:

Table 4-14: Somalia Classification Scores

	Core	Rim	Gap
Somalia Scores	320.000	316.774	326.436

Since Somalia scores highest with the Gap function, we would label it as such. Alternatively, we could use the canonical discriminant functions which are the orthogonal mappings of the observations in discriminant function space. We calculate the canonical discriminant function scores for each country and determine which group centroid the country is closest too. The two methods result in identical classifications.

In the case of Somalia, our classification agrees with Barnett's. Looking at all countries, we see that the 10-variable model achieves the following accuracies.

Table 4-15: 10-Variable Model Confusion Matrix

from \ to	Core	Rim	Gap	Total	% correct
Core	43	1	7	51	84.31%
Rim	2	17	0	19	89.47%
Gap	17	14	99	130	76.15%
Total	62	32	106	200	79.50%

As with all models we explored, our final model does well at classifying Core and Rim states, but has higher variability with Gap countries. There are two possible reasons for misclassification; either our model is insufficient to correctly classify all states, or the original classifications were incorrect. That is, perhaps Barnett's Core, Rim, Gap classifications vary from classifications of Stable, Borderline, Failing states. It is important at this point to revisit our original classification and investigate the countries which are being misclassified. Table 4-16 shows the states misclassified by our final model, and the probabilities of belonging to each group.

Table 4-16: Nations Misclassified Using 10-Variable Model

Observation	Barnett	Model	Pr(Core)	Pr(Rim)	Pr(Gap)
Belarus	Core	Gap	0.450	0.055	0.495
Fiji	Core	Gap	0.311	0.018	0.671
Malta	Core	Gap	0.478	0.001	0.521
Moldova	Core	Gap	0.307	0.007	0.686
Mongolia	Core	Gap	0.162	0.033	0.805
Tonga	Core	Gap	0.031	0.001	0.968
Vanuatu	Core	Gap	0.224	0.000	0.776
Hong Kong	Core	Rim	0.323	0.630	0.047
Andorra	Gap	Core	0.961	0.001	0.039
Barbados	Gap	Core	0.811	0.000	0.189
Bosnia and Herzegovina	Gap	Core	0.608	0.001	0.391
Bulgaria	Gap	Core	0.782	0.008	0.210
Cayman Islands	Gap	Core	0.943	0.000	0.057
Costa Rica	Gap	Core	0.559	0.270	0.171
Croatia	Gap	Core	0.758	0.030	0.212
Cyprus	Gap	Core	0.918	0.000	0.082
Israel	Gap	Core	0.726	0.009	0.266
Macedonia	Gap	Core	0.514	0.001	0.485
Mauritius	Gap	Core	0.532	0.062	0.407
Palau	Gap	Core	0.744	0.005	0.251
Puerto Rico	Gap	Core	0.667	0.002	0.331
Romania	Gap	Core	0.562	0.396	0.042
Serbia	Gap	Core	0.738	0.001	0.260
Singapore	Gap	Core	0.762	0.017	0.221
Tunisia	Gap	Core	0.387	0.271	0.342
Bangladesh	Gap	Rim	0.005	0.710	0.285
Brunei	Gap	Rim	0.355	0.439	0.206
Colombia	Gap	Rim	0.117	0.524	0.359
Ecuador	Gap	Rim	0.085	0.822	0.093
Egypt	Gap	Rim	0.020	0.924	0.056
Iran	Gap	Rim	0.000	0.997	0.003
Nigeria	Gap	Rim	0.007	0.653	0.339
Paraguay	Gap	Rim	0.001	0.957	0.042
Peru	Gap	Rim	0.055	0.893	0.052
Qatar	Gap	Rim	0.300	0.505	0.195
Sudan	Gap	Rim	0.001	0.669	0.330
Syria	Gap	Rim	0.007	0.912	0.080
United Arab Emirates	Gap	Rim	0.037	0.928	0.036
Venezuela	Gap	Rim	0.035	0.695	0.270
Chile	Rim	Core	0.540	0.402	0.057
Greece	Rim	Core	0.916	0.055	0.029

Recall that had we used our entire set of 60 variables, we would have achieved approximately 90% accuracy, compared to the 80% accuracy of the 10-variable model. The difference in classifications can be thought of as the risk associated with using a reduced variable set. Table 4-17 shows the countries misclassified using the full model.

Table 4-17: Nations Misclassified Using Full Model

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)
New Caledonia	Core	Gap	0.258	0.742	0.000
Andorra	Gap	Core	0.975	0.025	0.001
Barbados	Gap	Core	0.775	0.225	0.000
Bosnia and Herzegovina	Gap	Core	0.604	0.396	0.000
Costa Rica	Gap	Core	0.969	0.030	0.000
Croatia	Gap	Core	0.992	0.008	0.000
Cyprus	Gap	Core	0.971	0.029	0.000
Kuwait	Gap	Core	0.566	0.432	0.002
Palau	Gap	Core	0.712	0.276	0.012
Puerto Rico	Gap	Core	0.577	0.423	0.000
Romania	Gap	Core	0.999	0.001	0.000
Serbia	Gap	Core	0.790	0.210	0.000
Bangladesh	Gap	Rim	0.002	0.131	0.867
Egypt	Gap	Rim	0.001	0.027	0.973
Iran	Gap	Rim	0.000	0.006	0.994
Lesotho	Gap	Rim	0.010	0.077	0.913
Paraguay	Gap	Rim	0.001	0.450	0.549
Peru	Gap	Rim	0.001	0.030	0.969
Syria	Gap	Rim	0.009	0.167	0.825

The three countries highlighted in bold, New Caledonia, Kuwait, and Lesotho, were misclassified by the full model, but not by the reduced model. Of the 41 states misclassified by the reduced model, 16 were still misclassified when all 60 variables were used, all but one of which was previously classified as a Gap Country. This suggests the possibility that these 16 were not correctly classified initially. It remains for the decision maker to decide whether or not the additional resources required to collect data on the 50 extra variables is worth the gain of improving the model's accuracy by 10%. Recall too that accuracy equivalent to that of the full model may be achieved with the ten variables if alternate discriminant functions are used. Furthermore, the Barnett classification is used only as a proxy for state stability.

We can further analyze the classifications of various countries graphically. Using the standardized canonical discriminant function coefficients, we can plot countries in Discriminant Function Space. As with FA, the Canonical Discriminant Functions can be characterized according the variables loading heavily in each dimension.

Figure 4-3 provides a visual representation of the variables most useful for discriminating on each dimension. It shows the direction, in discriminant function space, and magnitude of the correlations between the variables and the discriminant functions.

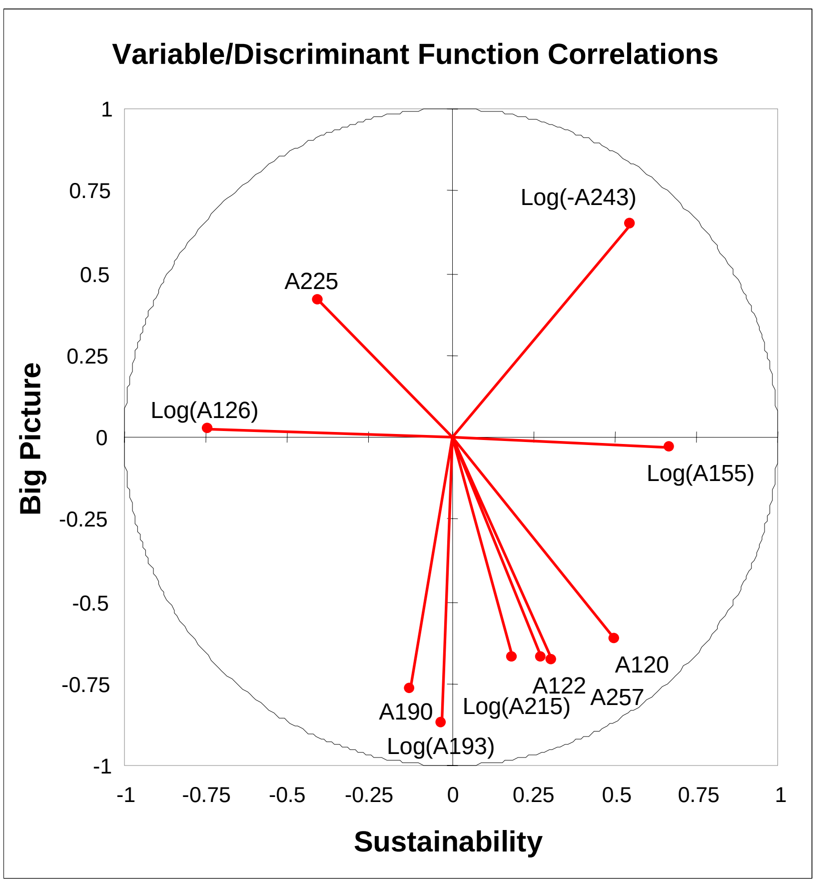

Figure 4-3: Correlations of Variables with Discriminant Functions

We see that the first discriminant function is most heavily influenced by the three variables identified earlier; Imports, Foreign Aid, and Land Area. Recall from the Factor Analysis that these three variables comprised the second principal factor which we labeled "Sustainability". Other variables also provide some input into this dimension, but a few are far more critical to the second dimension. Six of the variables loading heavily on the second discriminant function also loaded heavily on the first principal factor we called "The Big Picture". These are Imports, Political Terror, Population aged 18-22, Tuberculosis Death Rate, Percent of People Undernourished, and Child Mortality Rate.

It is no coincidence that the first two Principal Factors correspond to the two discriminant functions. Both techniques attempt to discover the underlying structure of the data by finding linear combinations which form mutually orthogonal functions. It should not be surprising then that the two methods produce similar pictures of the data's true structure. Furthermore, we should expect that the variables we found to explain the most variation in the dataset would also be most useful for classifying states. Table 4-18 provides the Canonical Discriminant Functions.

Table 4-18: Canonical Discriminant Functions

	Discriminant Function 1	Discriminant Function 2
Intercept	-5.057	-4.498
Log(-A243)	0.152	0.234
Log(A193)	-0.266	-0.544
Log(A126)	-0.296	0.146
A120	0.240	-0.208
A190	-0.013	-0.005
Log(A155)	0.172	0.049
A257	24.570	-0.791
Log(A215)	0.442	0.040
A225	-0.049	0.007
A122	-0.151	-0.177

Note that the coefficient corresponding to Tuberculosis Death Rate has a counterintuitive positive sign. One would expect that a lower number of deaths due to Tuberculosis would be better for a nations overall status. Montgomery *et al* describe three reasons that may explain a variable having the "wrong" sign in this or any regression model. If the range of one of the regressors is small in relation to other variables in the model, the variance in the estimate of the regression coefficient will be large, resulting in a lower confidence estimate. In this situation, the range of the Tuberculosis data is (-1.204, 5.596) compared to, for example the range of the Child Mortality Rate which is (3, 283). Another reason for the positive sign could be severe multicollinearity which can also increase the variance of the coefficient estimates, again increasing the probability of seeing a counterintuitive sign. Finally, either one or more important regressors may be left out of the model, or other regressors in the model are causing the sign to change. The coefficients measure the effects of a variable given that each of the other variables is in the model. In other words, it may be that Tuberculosis Deaths do have a negative effect on Function 2 scores if considered alone, but with other variables already in the model, the net effect on that function may be positive (Montgomery *et al*, 2001: 120-2). This appears to be the most likely cause of the positive Tuberculosis Death Rate coefficient in this case. When all 60 variables are used, we see that in fact the sign is negative, and Tuberculosis has a coefficient of -0.512. This suggests that the particular combination of variables used in the reduced model causes the Function 2 coefficient for Tuberculosis to change sign.

A sample of selected countries is plotted in Figure 4-4. The ellipses represent 95% confidence intervals around the group centroids.

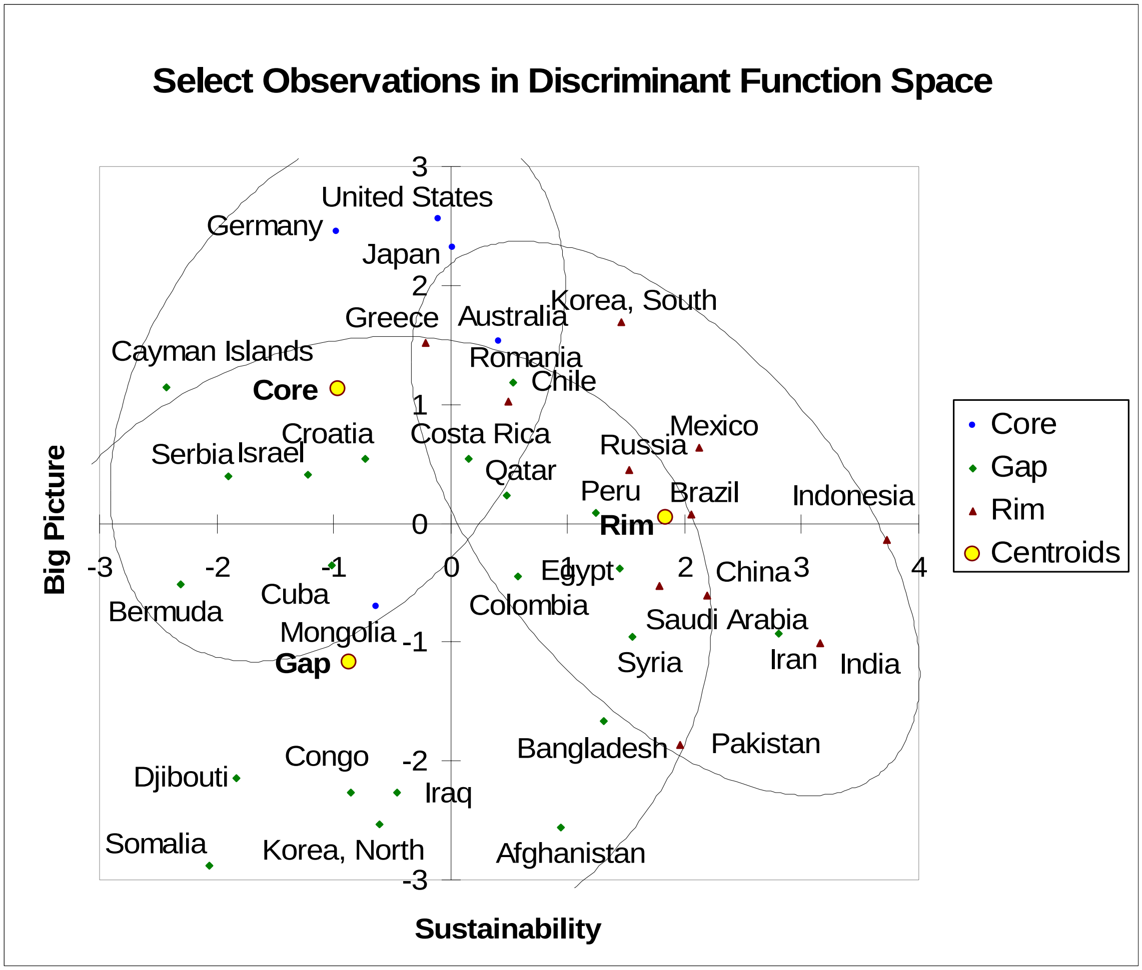

Figure 4-4: Classification of States

It is clear from the figure that it is indeed more difficult to classify Gap countries. In fact, we see that the 95% confidence interval around the Gap centroid actually contains the other group centroids. We also see that there is a wider spread of countries which were pre-classified as Gap.

Recall that for the three group case, two discriminant functions are used. While our model may not correctly identify every Gap state defined by Barnett, there does appear to be a distinct separation of the extremely critical nations by the second discriminant function, shown on the vertical scale. Countries scoring lowest in this dimension include Somalia, Djibouti, Congo, Iraq, Afghanistan, and North Korea, while Germany, Japan and the United States score highest. It appears then that we may have a useful model for identifying the most critical nations, and for selecting states for further analysis.

To achieve a high score on Function 2, the Big Picture Function, a country would need high values for variables with positive coefficients, and low values for variables with negative coefficients. Looking at two examples, we see from Table 4-16 that Israel was predefined to be a Gap country, but was classified by our model as being part of the Core. Conversely, Mongolia, which was originally classified a Core country, has now been classified as a Gap country. Table 4-19 provides data for each of these countries, their scores from the second discriminant function, as well as summary statistics for all countries analyzed. The values in parenthesis are the "worst" of Israel, Mongolia, and the Mean.

Table 4-19: Comparison of Function 2 Scores for Israel and Mongolia

	Function 2 Coefficients	Israel	Mongolia	Mean (All)	St. Dev. (All)
Intercept	-4.498	1	1		
Imports	0.234	24.502	(20.619)	22.545	2.233
Pop. Undernourished	-0.544	2.197	(3.332)	2.175	1.013
Foreign Aid	0.146	4.255	4.646	(3.214)	1.694
Political Terror (Lower is Better)	-0.208	(4.000)	2.000	2.560	1.069
Child Mortality (Per 1000)	-0.005	6.000	52.000	(59.070)	65.864
Land Area	0.049	(9.986)	14.264	11.265	2.648
Pop % Aged 18-22	-0.791	0.081	(0.107)	0.088	0.017
Tuberculosis Deaths	0.040	(-0.105)	3.186	2.174	1.641
Women Share of Workplace	0.007	49.600	50.300	(39.211)	11.524
Political Rights (Lower is Better)	-0.177	1.000	2.000	(3.295)	2.117
Function 2 Scores		0.407	-0.708	-0.466	

Recall that several of the variables in the model were transformed to more closely resemble a normal distribution. This transformation explains, for example, the negative value for Tuberculosis Death Rate for Israel. This means their value was low, but not actually negative. Israel scores lower than the mean in three of the ten categories, but scores high enough in other areas to compensate, and as a result still receives a Core classification. The fact that Barnett classified Israel as a Gap country may be due more to its proximity to other troubled nations, which is a factor not included in our dataset. Mongolia scores poorly, at least one standard deviation from the mean, in three areas including Level of Imports, Percentage of the Population Undernourished, and Percentage of the Population aged 18-22. These appear to be the primary reasons for its Gap classification. Similar specific analyses can be conducted for any nation of interest in this study.

The first discriminant function, shown on the horizontal axis of Figure 4-3, separates Rim countries from Core and Gap countries. As our confusion matrices confirm, it appears to be easiest to segregate the Rim countries from the others. At first glance, it may seem counter-intuitive that it is easier to identify the states which are by definition hard to categorize. However, such speculation assumes that all countries lie in only the one dimension, represented by the vertical axis. While Rim states do lie between Gap and Core states in the second dimension, there are differences in other dimensions that must be considered. Reexamining Table 4-12 provides insight into which variables are particularly useful for identifying Rim states.

Table 4-20: Discriminant Functions (Repeat of Table 4-12)

	Core	Rim	Gap
Intercept	-319.417	-329.287	-309.575
Log(-A243)	19.071	19.242	18.550
Log(A193)	12.654	12.497	13.871
Log(A126)	6.598	5.610	6.234
A120	-6.750	-5.854	-6.250
A190	0.155	0.125	0.165
Log(A155)	-1.727	-1.300	-1.823
A257	1684.570	1754.207	1688.771
Log(A215)	-6.903	-5.709	-6.951
A225	1.005	0.861	0.984
A122	1.392	1.160	1.782

Several variables appear to have similar coefficients for Gap and Core countries, but are different for Rim countries. Adjusting the three group model, we built a discriminant function to classify states only as either Rim or Non-Rim. As shown in Table 4-21, the Sustainability variables dealing with Imports, Foreign Aid, and Land Area are very significant for distinguishing Rim states from the other groups.

Table 4-21: Significance of Variables for Distinguishing Rim Countries

Variable	F	DF1	DF2	p-value
Log(-A243)	123.445	1	198	< 0.0001
Log(A126)	114.995	1	198	< 0.0001
Log(A155)	105.982	1	198	< 0.0001
A120	19.811	1	198	< 0.0001
A190	14.159	1	198	0.000
A225	12.670	1	198	0.000
Log(A193)	8.430	1	198	0.004
A257	3.491	1	198	0.063
Log(A215)	1.892	1	198	0.171
A122	0.074	1	198	0.786

Therefore, it appears we have a two function model. One function separates the Rim countries, while the other distinguishes between The Gap and The Core.

4.4. Discriminant Analysis – Fund for Peace

Our final task was to determine if the variables selected for our final model were indeed sufficient for classifying failing states, or if their usefulness was unique to Barnett's classifications. To test this, we applied the same DA techniques to the Fund for Peace (FFP) 2006 Failed States Index. Recall the FFP publishes an annual Index which provides scores for each country indicating their current stability.

The FFP provided scores for 146 of the 200 countries previously analyzed, so only those nations were used in this analysis. For consistency's sake, we divided the nations into three groups. The states are given a score on a scale from 0 to 120 in the FFP data, but are given no categorical assignment. We, therefore needed to choose cut-off points for each class. As shown in Table 4-5, the scores themselves do not seem to provide natural break points between classes.

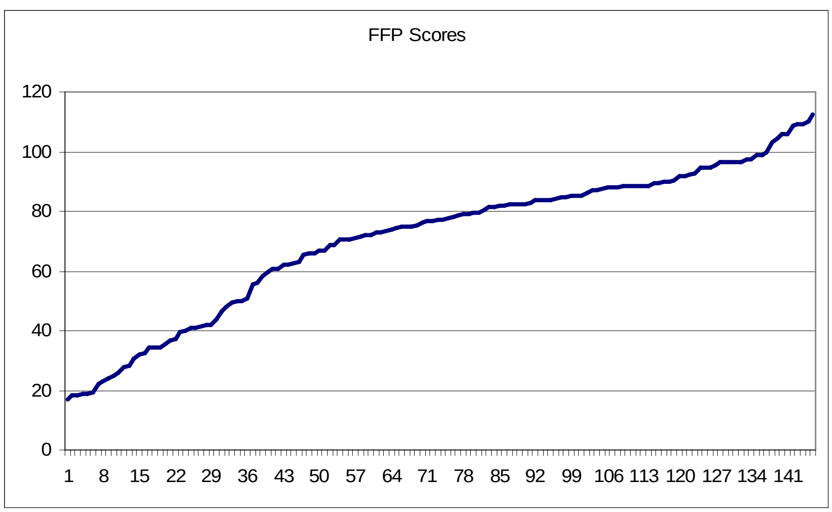

Figure 4-5: Fund for Peace Scores

Lacking clear breakpoints, the nations were simply divided into three groups, as close to equal size as possible. Group 1 consisted of nations posing the highest risk of failing, Group 2 countries were considered medium risk, and Group 3 was made up of the most stable countries having the lowest risk of state failure.

We proceeded in the same manner as before, foregoing the variable selection process. Using the ten variables from our final model, we achieved the results in Table 4-22. States pre-classified as High, Medium and Low risk are analogous, but certainly not equivalent, to the Gap, Rim, and Core classifications from Barnett.

Table 4-22: Confusion Matrix using Fund for Peace Classification

from \ to	High	Med	Low	Total	% correct
High	38	10	0	48	79.17%
Med	7	38	4	49	77.55%
Low	0	8	41	49	83.67%
Total	45	56	45	146	80.14%

We first notice that the Discriminant Function constructed using the same ten variables again achieves approximately 80% accuracy. Just as the discriminant function used on Barnett's classification was better at classifying Core and Rim states, this function appears to do slightly better with the Low Risk nations. One notable improvement is that no countries previously identified as Low Risk were classified as High Risk, and vice-versa. The ambiguities all appear within the Medium Risk classifications.

Examining the Discriminant Functions themselves, we see definite consistencies between the FFP and Barnett models. Figure 4-6 shows the variable-function correlations.

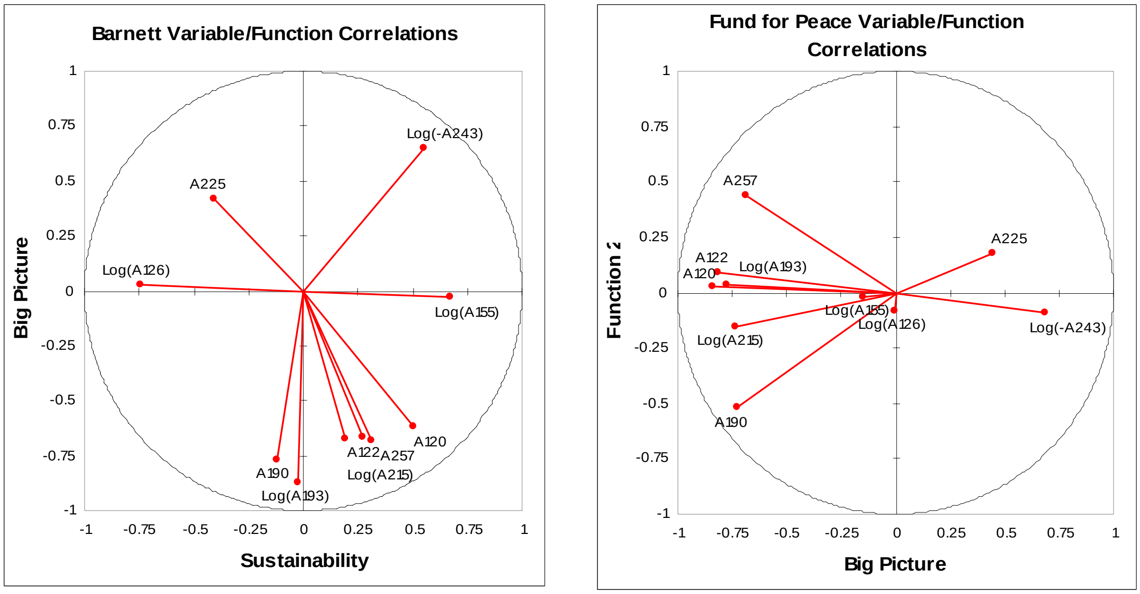

Figure 4-6: Comparison of Discriminant Function Structure

Fundamentally, the structure of the data remains the same. However, the orientation has rotated 90 degrees clockwise. Therefore, the Big Picture function, represented by the second discriminant function under the Barnett case, is now the first function, shown on the horizontal axis. We notice also that the variables most heavily loaded on the Sustainability Function before have all but disappeared in the new model as evidenced by the shorter radii. In fact, these variables are not significant to the model at the .05 alpha level. This is not surprising as we have already determined that this function is orthogonal to the Big Picture function, and should therefore not be expected to substantially contribute to discrimination along the inherently one dimensional Failed States Index. Our original Function 2 seems to capture the majority of what the Fund for Peace uses to classify states according to their likelihood of failure.

Table 4-23 shows a comparison between the discriminant functions derived from using both prior classifications.

Table 4-23: Comparison of Discriminant Functions

Barnett Discriminant Functions		
	F1	**F2**
Intercept	-5.057	**-4.498**
Log(-A243)	0.152	**0.234**
Log(A193)	-0.266	**-0.544**
Log(A126)	-0.296	**0.146**
A120	0.240	**-0.208**
A190	-0.013	**-0.005**
Log(A155)	0.172	**0.049**
A257	24.570	**-0.791**
Log(A215)	0.442	**0.040**
A225	-0.049	**0.007**
A122	-0.151	**-0.177**

FFP Discriminant Functions		
	F1	F2
Intercept	**-1.504**	-0.403
Log(-A243)	**0.229**	-0.197
Log(A193)	**-0.358**	0.495
Log(A126)	**0.011**	-0.011
A120	**-0.782**	0.006
A190	**-0.003**	-0.018
Log(A155)	**-0.018**	0.086
A257	**4.181**	39.356
Log(A215)	**0.050**	-0.134
A225	**0.007**	0.018
A122	**-0.320**	0.023

The two columns in bold represent the Big Picture function for each of the respective cases. On inspection, the two functions appear quite similar. The only noticeable difference is variable 257, Percentage of the Population aged 18-22. This variable now has a positive coefficient suggesting that a greater percentage of people of this age improves national stability. However, previously discussed issues with the scale of this variable may account for this discrepancy.

Considering the similarities between the two functions, we would expect a plot of observations in the new Discriminant Function space to be similar to the original, except rotated. This situation is seen in Figure 4-7.

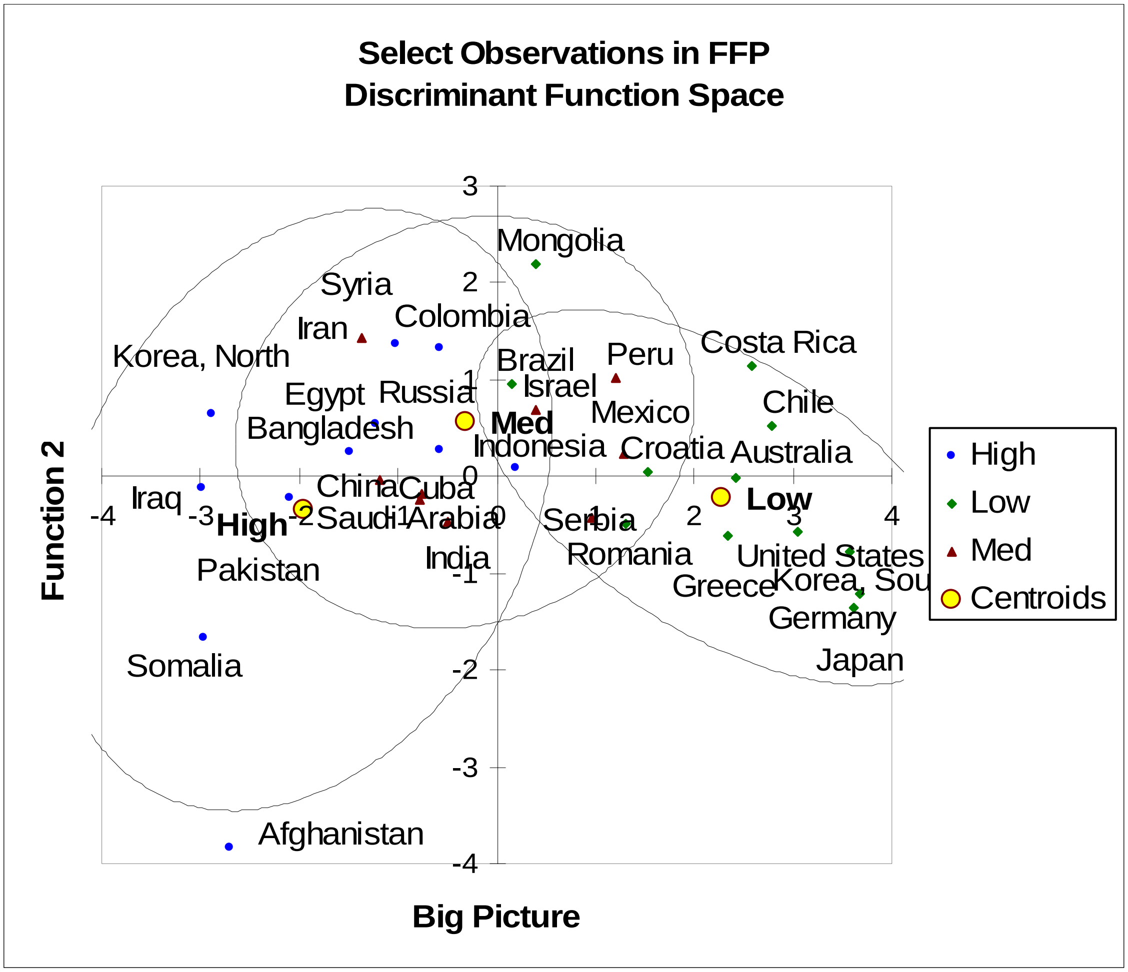

Figure 4-7: Classification of States - FFP

The position of countries along the horizontal in this plot is highly coincident with the vertical axis from the Barnett case. We also see that the Medium Risk centroid is much closer to being directly between the other two groups, again suggesting the one-dimensionality of the Failed States Index.

Most countries are positioned in conjunction with their original locations from the previous observation plot. The one notable exception is Afghanistan which is now far removed from the rest of the countries, due to its unusually low “New Function 2” score.

Upon closer examination, we see from Figure 4-6 that the variable most heavily loaded in this dimension is 190, Child Mortality Rate. Afghanistan ranked third from the bottom across all 200 nations observed, with a rate of 257 deaths per 1000 children under five years of age. The two countries scoring worse, Sierra Leone and Angola, are not plotted. Afghanistan's Child Mortality Rate represents a three standard deviation departure from the mean of 59 per 1000.

Appendix E provides a comparison between the 2006 FFP Index and the scores each nation received on the Big Picture Function resulting from Barnett's classification.

4.5. Failing States

The preceding analyses appear promising for aiding in our goal of identifying those states most likely to be considered failing. Both FA and DA highlighted a quantifiable dimension that provides a documented, tractable analysis of the overall status of nations. This dimension is characterized by the Big Picture factor, and well measured by the second discriminant function when Barnett's initial classification was used, and the first discriminant function when we used the FFP Failed States Index. States which have very low scores on either of these functions may be those most in danger of failing and should be subjected to further analysis by stability experts. Table 4-22 is a ranked listing of the 30 nations scoring lowest on our final model, along with their Prior and Posterior classifications. Whether or not these nations are indeed most in need of intervention is left to experts in other fields. This analysis provides analytic support to the idea that there are substantial differences between these and other nations of the world, and a way to quantify those differences. It offers a quantitative method to screen states for further analysis based on the collection of a parsimonious set of indicators.

Table 4-24: States with Lowest Function 2 Scores

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	F2
Burundi	Gap	Gap	0.001	0.999	0.000	-2.322	-3.356
Congo, DRC	Gap	Gap	0.001	0.997	0.002	-0.681	-3.147
Sierra Leone	Gap	Gap	0.001	0.999	0.000	-3.913	-3.120
Haiti	Gap	Gap	0.001	0.997	0.002	-0.743	-3.017
Equatorial Guinea	Gap	Gap	0.001	0.999	0.000	-3.121	-2.980
Rwanda	Gap	Gap	0.001	0.999	0.000	-2.783	-2.952
Eritrea	Gap	Gap	0.001	0.998	0.001	-1.169	-2.904
Somalia	Gap	Gap	0.002	0.998	0.000	-2.059	-2.882
Zimbabwe	Gap	Gap	0.001	0.776	0.223	1.046	-2.860
Guinea-Bissau	Gap	Gap	0.002	0.998	0.000	-3.339	-2.857
Chad	Gap	Gap	0.002	0.990	0.008	-0.324	-2.767
Togo	Gap	Gap	0.002	0.996	0.003	-0.741	-2.753
Angola	Gap	Gap	0.002	0.998	0.000	-1.790	-2.748
Comoros	Gap	Gap	0.003	0.997	0.000	-2.676	-2.661
Central African Republic	Gap	Gap	0.003	0.996	0.000	-1.447	-2.565
Afghanistan	Gap	Gap	0.002	0.762	0.236	0.940	-2.560
Malawi	Gap	Gap	0.003	0.987	0.010	-0.348	-2.535
Korea, North	Gap	Gap	0.003	0.992	0.005	-0.604	-2.529
Cameroon	Gap	Gap	0.003	0.992	0.005	-0.575	-2.526
Tajikistan	Gap	Gap	0.004	0.996	0.000	-2.166	-2.472
Niger	Gap	Gap	0.004	0.996	0.000	-1.585	-2.468
Ethiopia	Gap	Gap	0.004	0.994	0.002	-1.049	-2.418
Yemen	Gap	Gap	0.003	0.758	0.239	0.884	-2.418
Liberia	Gap	Gap	0.005	0.995	0.000	-2.816	-2.396
Guinea	Gap	Gap	0.005	0.995	0.000	-1.755	-2.393
Uzbekistan	Gap	Gap	0.005	0.979	0.017	-0.237	-2.330
Nepal	Gap	Gap	0.003	0.705	0.292	0.944	-2.330
Sudan	Gap	Rim	0.001	0.330	0.669	1.525	-2.314
Congo	Gap	Gap	0.006	0.991	0.003	-0.854	-2.271
Iraq	Gap	Gap	0.006	0.985	0.010	-0.461	-2.264

4.6. Chapter Summary

This chapter outlines the results of the various analyses performed in this study. The combined results of the Factor Analysis and Discriminant Analysis provide several key insights to assist in identifying failing or failed states.

There are in fact statistically significant differences between countries which have been previously classified as Core, Gap, or Rim across a wide range of available data.

Furthermore, the discriminant function which separates the Gap and Core countries appears useful for our purpose of distinguishing failing and borderline states from more stable nations, and provides a scale on which to measure their instability. Furthermore, the differences between states are detectable and measurable using as few as ten carefully chosen variables, which are currently being collected by various agencies and available open source. One such set of variables is as follows:

Value of Imports
Percentage of Population Undernourished
Amount of Foreign Aid
Political Terror Rating
Children Under Five Mortality Rate
Land Area
Youth Bulge – Percentage of People Aged 18-22
Tuberculosis Death Rate
Percentage of Women Comprising the Workplace
Political Rights

Using these variables, with appropriate transformations, states may be categorized in terms of their overall status by multiplying a country's value on each of these variables by the classification matrix shown in Table 4-23, and assigning it to the group receiving the highest score.

Table 4-25: Discriminant Functions

	Core	Rim	Gap
Intercept	-319.417	-329.287	-309.575
Log(-A243)	19.071	19.242	18.550
Log(A193)	12.654	12.497	13.871
Log(A126)	6.598	5.610	6.234
A120	-6.750	-5.854	-6.250
A190	0.155	0.125	0.165
Log(A155)	-1.727	-1.300	-1.823
A257	1684.570	1754.207	1688.771
Log(A215)	-6.903	-5.709	-6.951
A225	1.005	0.861	0.984
A122	1.392	1.160	1.782

In addition, multiplying by the appropriate canonical function shown in Table 4-24, we obtain a Big Picture score indicating the likelihood a country may be in crisis.

Table 4-26: Canonical Discriminant Functions

Variable	Big Picture Function
Intercept	-4.498
Imports	0.234
Pop. Undernourished	-0.544
Foreign Aid	0.146
Political Terror	-0.208
Child Mortality (Per 1000)	-0.005
Land Area	0.049
Pop % Aged 18-22	-0.791
Tuberculosis Deaths	0.040
Women Share of Workplace	0.007
Political Rights	-0.177

Countries scoring lowest are those we may consider most in danger of failing, and consequently becoming attractive to terrorist groups. This result is validated by the demonstrated ability to classify states on the crisis scale proposed by the Fund for Peace using these same variables. Furthermore, this list of key indicators suggests areas which may serve as focal points for international assistance. Finally, the methodology and analysis can be repeated using any available data or for any official classification of states to provide discrimination and screening of potential troubled areas for further study, aid, support, or intervention.

5. Conclusions and Recommendations

5.1. Introduction

This chapter concludes this study with a summary of the significant research contributions made through this effort, and some areas for future research.

5.2. Research Contributions

This thesis provides analytic support to the classification of states as Stable, Borderline, or Failing. It provides a list of key variables, available open source, which can be used to determine the crisis level of a nation, and a function for calculating this level. Both Factor Analysis and Discriminant Analysis are useful for exposing the true structure of the myriad of data available on states. DA has also been shown to be a valuable tool for identifying which states are more likely to require assistance. The data collection and analysis accomplished in this thesis lay the groundwork for identifying key areas of future concern for the US in the continuing hunt for terrorist cells.

5.3. Recommendations for Future Research

The following sections suggest some areas where additional gains could be made through future analysis. By no means does this represent an exhaustive list. The reader is encouraged to consider the possible applications of the methods discussed in this thesis, as well as additional techniques for predicting failing states.

5.3.1. Time-Series Analysis

Clearly, the true importance of this work will be realized if we can extend it to the *prediction* of failing states. To this point we have determined the variables or indicators most useful for classifying states as failing, marginal, or stable, and identified nations which have reached crisis stage. The next step is to examine the history of these states. Knowing what measures are most important, we can assess these indicators throughout the critical period when the nations fell. We can then use this information to identify states which are currently following the same negative trends. This has the potential to provide the international community several years advance notice in which to plan and carry out some form of intervention to prevent crises and the spread of terrorism. This should be the first priority of any follow-on effort.

5.3.2. Suggested Applications of Analysis Techniques

The techniques used to analyze nations in this thesis could easily be extended to myriad other groups. For example, we may be interested in our own country to identify states, cities, or areas within cities where we could expect economic depression or an outbreak in crime. The conditions leading to such circumstances are similar to those of failing states. On the international level, it is in our interests to closely follow the actions of transnational groups, which may or may not have terrorist tendencies. Throughout this study, much information on nations of the world was available, but very little open source data seems to be collected on non-nation groups. If possible, we may want to collect the key information identified in this study on these entities as well.

The US is also currently concerned with is reconstruction and stabilization of other nations. In Iraq, government agencies are struggling with defining clear objectives for the stabilization efforts, and measuring progress towards those objectives. As this thesis highlights several of the key indicators of state strength, there is an opportunity to contribute to the setting of goals and assessing the progress made in achieving them. Planners could use such analysis to prioritize reconstruction activities within countries.

For example, recall that the geographic size of a nation is one of the key indicators of stability found in this study. This might be due to the relationship between size and available economic or natural resources. This suggests partitioning Iraq into three smaller nations may be less desirable from a stability standpoint, though other factors such as ethnic fractionalization may suggest otherwise. In addition, the significance of Political Terror and Political Rights indicate that true stability in Iraq is more likely under a free and democratic government.

The principal factors that describe the status of a group are not exclusive to nations. In fact, the indicators considered in this thesis dealing with financial status, unemployment, indebtedness, health, freedom, a sense of justice, perception of opportunity, and so forth are the key variables we could use to assess any population, down to individuals. They constitute the needs of all people and could therefore provide insight into aiding the homeless, gangs, struggling children, employees or any other group of people we are interested in.

5.3.3. Alternative Missing Data Techniques

In studies involving time-series data, it would be beneficial to explore methods for imputing data across two or more dimensions. In this study, when data were missing on a variable for a given year, the missing values were drawn from other similar countries within the year of interest. However, we may achieve more accurate values in some cases if we were to draw from other years in which data were available for the incomplete country. Drawing exclusively from either an individual country's populated years, or from other countries will not necessarily always produce optimal results. If data are missing for a single year, interpolation may provide a more reasonable estimate than using data from another country, similar as that country may be. However, if data were rarely collected for a country, or only collected outside the time period of interest, extrapolation may produce less accurate results than using data from other countries. This may be particularly true if those countries have similar values on many other variables. Note also that imputing over time is only possible if data has been collected at least once on the country, which was not always the case in this study. Throughout our literature review, we discovered no such multi-dimensional imputation methods.

5.3.3.1. Multiple Imputation

Recall from Chapter 2 that Multiple Regression Imputation calculates estimates of missing values by using a regression equation built from the non-missing data. This approach to estimating missing values may be desirable in the sense that it uses all available data and relationships among variables to impute missing values, and two analysts working from the same incomplete dataset will generate the same imputed dataset for use in future analysis. However, as the imputed values are a linear function of the observed variables, the correlation among variables will necessarily be overstated (Allison, 2001: 29). Moreover, the deterministic nature of the procedure implies that it does not account for the uncertainty due to the missing data, thus variances and covariances may be underestimated (Allison, 2001: 28). Multiple Imputation (MI) is an imputation procedure which builds on this concept by including a variation factor along with the predicted value for each imputation. Each time a new value is imputed, it will include the variation inherent in the variable. This will allow us to create multiple complete datasets with variation in the imputed values for further analysis.

In general, we are not interested in multiple results for a single study, so the next step is to analyze each of the imputed datasets for the parameters of interest, and then combine the results into a single point estimate. Chantala and Suchindran offer a simple calculation for combining the results of multiple imputations (Chantala and Suchindran, 2006). In reality however, we can not know the true values of the population parameters. To account for this uncertainty, we should draw the values of the randomly from their Bayesian posterior distributions (Allison, 2001: 31). One method for estimating the posterior distributions of the parameters is the Data Augmentation Algorithm.

5.3.3.2. Data Augmentation

Data augmentation is an iterative algorithm for finding posterior distributions (Allison, 2001: 34). Allison, 2001 describes the algorithm as consisting of the following steps (Allison, 2001: 35).

0. Choose the variables for use in the imputation process. In addition to the variables for which we wish to impute data, other variables may be included if they are known to be highly correlated with, or have similar missing data patterns to, the variables of interest. Also, while MI has been shown to be robust to non-normally distributed data, the algorithm tends to converge faster for the multivariate normal model. Therefore, if possible, transform variables so that they at least approximately follow a normal distribution.
1. Choose starting values for the parameters. For the multivariate normal model, the parameters are the means and covariance matrix. Starting values can be gotten from the standard formulas using list-wise or pair-wise deletion.
2. Use the current values of the means and covariances to obtain estimates of regression coefficients for equations in which each variable with missing data is regressed on all observed variables. This is done for each pattern of missing data.

3. Use the regression estimates to generate predicted values for all the missing values. To each predicted value, ass a random draw from the residual distribution for that variable.
4. Using the “completed” dataset, with both observed and imputed values, recalculate the means and covariance matrix using standard formulas.
5. Based on the newly calculated means and covariances, make a random draw from the posterior distribution of the means and covariances.
6. Using the randomly drawn means and covariances, go back to Step 2 and continue cycling through the subsequent steps until convergence is achieved. The imputations that are produced during the final iteration are used to form a completed dataset.

Multiple Imputation with Data Augmentation is a technique which is gaining popularity as automated software is developed and tested. Analysts wishing to use our dataset for future studies may benefit from further exploration into this or other missing data techniques.

5.3.4. Alternative Discriminant Analysis Techniques

As shown in Chapter 4, there are several approaches to building a Discriminant Function. A quick look at the results obtained using Mahalanobis’ Method as opposed to Fisher’s suggests that greater classification accuracy may be achieved with a similar reduced set of variables by exploring other DA methods.

5.3.5. Cluster Analysis

Cluster Analysis (CA) is a technique used to partition a set of subjects into two or more disjoint groups (Lattin *et al*, 2003: 264-5, Dillon *et al*, 1984: 157-8). It does this by using information captured in a set of independent variables to create the clearest possible separation among the subjects, and assigning them to their most likely group (Lattin *et al*, 2003: 265). CA compares the within-group variation to the between group variation, reassigning members until the former is as small as possible in relation to the latter (Dillon *et al*, 1984: 160).

Recall from the discussion of Factor Analysis section that one of its primary objectives is to reduce the dimensionality of a dataset. FA does this by grouping variables which seem to reflect an underlying, latent factor. Similarly, CA may also be thought of as a data reduction technique. However, rather than grouping variables (columns) of a data matrix, the number of distinct observations (rows) is reduced to a smaller number of observation clusters (Dillon *et al*, 1984: 161). If CA could be used to effectively categorize the 200+ nations of the world into three or four distinct classes, analysts would then be left only to decide which category appears to contain the majority of critical states. Members of this cluster would then be candidates for being considered failing. Clearly, other multivariate and operations research techniques can be applied to improve our ability to aid subject matter experts and decision makers in the analysis and classification of failing states.

5.4. Conclusions

Due to the unwavering commitment of terrorist organizations, it appears the Global War on Terrorism will not end until we are able to disrupt their activities and preclude them from recruiting additional personnel. This can best be accomplished by taking a proactive approach in areas most likely to provide safe havens for terrorist groups looking for asylum. This thesis provides a foundation for such efforts by first identifying the key indicators of state failure through Factor Analysis and Discriminant Analysis. DA is then further used to determine the likelihood that a state will experience some form of crisis by constructing a discriminant function based on the appropriate variables. A list of ten variables and the appropriate classification functions based on these indicators are provided along with suggestions for their utilization in future studies. It is our hope that this will enable the international community to predict likely trouble spots and employ specific, targeted economic or political measures to prevent crises and thwart the spread of terrorism. Doing so will save time, money, and most importantly lives by addressing the issues likely to lead to costly violent conflict.

Appendix A: Initial Variables Considered

This appendix provides a list of all variables collected for the initial dataset used in this thesis, as well as the sources of the data. Series names are annotated with superscripts corresponding to one of the following sources:

1. CSCW - Centre for the Study of Civil War
2. EM-DAT: OFDA/CRED International Disaster Database: Centre for Research on the Epidemiology of Disasters
3. Freedom House
4. Dr. Mark Gibney, University of North Carolina, Center for International Studies
5. Sean O'Brien – Center for Army Analysis
6. Polity IV Database - Center for Global Policy at George Mason University
7. RAND
8. UN Millennium Development Group
9. UN Office on Drugs and Crime
10. UN Common Database
11. UN Population Division, World Population Prospects, 2003
12. UN High Committee on Refugees
13. UN Statistics Division
14. UNESCO
15. World Bank

Code	Data Availability	Series
100	98%	Population [11]
101	95%	School age population. Primary. Total [14]
102	95%	School age population. Primary. Male [14]
103	95%	School age population. Secondary. Total [14]
104	95%	School age population. Secondary. Male [14]
105	95%	School age population. Tertiary. Total [14]
106	95%	School age population. Tertiary. Male [14]
107	94%	Enrolment in total secondary. Public and private. All programmes. Total [14]
108	94%	Enrolment in primary. All grades. Total [14]
109	85%	Pupil-teacher ratio. Secondary [14]
110	77%	Public expenditure on education as % of GDP [14]
111	73%	Calories [5]
112	75%	Youth Bulge [5]
113	73%	Largest Religion % [5]
114	74%	Largest Ethnic Group % [5]
115	72%	Trade [5]

Code	Data Availability	Series
116	75%	% time in conflict 90-2003 [5]
117	100%	Battle Deaths (Zero when empty) [1]
118	73%	Refugees [12]
119	98%	GDP Per Capita [13]
120	82%	Political Terror [4]
121	92%	Freedom of Press [3]
122	91%	Political Rights [3]
123	91%	Civil Liberties [3]
124	92%	Agricultural land (% of land area) [15]
125	84%	Agriculture, value added (% of GDP) [15]
126	81%	Aid per capita (current US$) [15]
127	82%	Arms imports (constant 1990 US$) [15]
128	84%	Births attended by skilled health staff (% of total) [15]
129	90%	CO2 emissions (metric tons per capita) [15]
130	79%	Consumer price index (2000 = 100) [15]
131	69%	Contraceptive prevalence (% of women ages 15-49) [15]
132	62%	Electric power consumption (kWh per capita) [15]
133	61%	Energy imports, net (% of energy use) [15]
134	66%	Expenditure per student, primary (% of GDP per capita) [15]
135	87%	Exports of goods and services (% of GDP) [15]
136	77%	Exports of goods and services (annual % growth) [15]
137	73%	Exports of goods and services (constant 2000 US$) [15]
138	65%	External debt, total (DOD, current US$) [15]
139	92%	Fertility rate, total (births per woman) [15]
140	93%	Fixed line and mobile phone subscribers (per 1,000 people) [15]
141	81%	Food imports (% of merchandise imports) [15]
142	90%	Forest area (% of land area) [15]
143	88%	GDP per capita (constant 2000 US$) [15]
144	90%	GDP per capita growth (annual %) [15]
145	88%	GNI per capita, Atlas method (current US$) [15]
146	81%	GNI per capita, PPP (current international $) [15]
147	90%	Health expenditure per capita (current US$) [15]
148	71%	Hospital beds (per 1,000 people) [15]
149	89%	Households with television (%)[15]
150	90%	Immunization, measles (% of children ages 12-23 months) [15]
151	83%	Improved water source (% of population with access) [15]
152	90%	Inflation, GDP deflator (annual %) [15]
153	69%	International tourism, expenditures (% of total imports) [15]
154	94%	Internet users (per 1,000 people) [15]
155	93%	Land area (sq. km) [15]
156	92%	Life expectancy at birth, total (years) [15]
157	55%	Literacy rate, adult total (% of people ages 15 and above) [15]

Code	Data Availability	Series
158	52%	Literacy rate, youth total (% of people ages 15-24) [15]
159	75%	Military expenditure (% of GDP) [15]
160	81%	Military personnel (% of total labor force) [15]
161	93%	Mobile phone subscribers (per 1,000 people) [15]
162	89%	Mortality rate, infant (per 1,000 live births) [15]
163	89%	Mortality rate, under-5 (per 1,000) [15]
164	89%	Net migration [15]
165	81%	Personal computers (per 1,000 people) [15]
166	92%	Population density (people per sq. km) [15]
167	95%	Population growth (annual %) [15]
168	44%	Poverty headcount ratio at $2 a day (PPP) (% of population) [15]
169	70%	Prevalence of HIV, total (% of population ages 15-49) [15]
170	79%	Primary completion rate, female (% of relevant age group) [15]
171	80%	Primary completion rate, total (% of relevant age group) [15]
172	89%	Proportion of seats held by women in national parliament (%)[15]
173	61%	Public spending on education, total (% of government expenditure) [15]
174	87%	Pupil-teacher ratio, primary [15]
175	80%	Ratio of female to male enrollments in tertiary education [15]
176	88%	Ratio of female to male primary enrollment [15]
177	87%	Ratio of girls to boys in primary and secondary education (%)[15]
178	78%	Refugee population by country or territory of asylum [15]
179	96%	Rural population (% of total population) [15]
180	93%	Rural population growth (annual %) [15]
181	86%	Telecommunications revenue (% GDP) [15]
182	60%	Total debt service (% of exports of goods, services and income) [15]
183	63%	Unemployment, male (% of male labor force) [15]
184	65%	Unemployment, total (% of total labor force) [15]
185	96%	Urban population (% of total) [15]
186	65%	Use of IMF credit (DOD, current US$) [15]
187	85%	Maternal mortality ratio per 100,000 live births [8]
188	89%	Total number of seats in national parliament [8]
189	88%	Seats held by women in national parliament, percentage [8]
190	92%	Children under five mortality rate per 1,000 live births [8]
191	92%	Infant mortality rate (0-1 year) per 1,000 live births [8]
192	91%	Children 1 year old immunized against measles, percentage [8]
193	70%	Population undernourished, percentage [8]
194	97%	Land area covered by forest, percentage [8]
195	82%	Births attended by skilled health personnel, percentage [8]
196	69%	AIDS deaths [8]
197	44%	Population below $1 (PPP) per day consumption, percentage [8]
198	31%	Population below national poverty line, total, percentage [8]
199	44%	Poverty gap ratio [8]

Code	Data Availability	Series
200	78%	Net enrolment ratio in primary education, both sexes [8]
201	60%	Percentage of pupils starting grade 1 reaching grade 5, both sexes [8]
202	52%	Youth unemployment rate, aged 15-24, men [8]
203	95%	Telephone lines and cellular subscribers per 100 population [8]
204	95%	Internet users per 100 population [8]
205	80%	Personal computers [8]
206	91%	Gender Parity Index in primary level enrolment [8]
207	90%	Gender Parity Index in secondary level enrolment [8]
208	80%	Gender Parity Index in tertiary level enrolment [8]
209	88%	Protected area to total surface area, percentage [8]
210	99%	Tuberculosis prevalence rate per 100,000 population [8]
211	89%	Tuberculosis treatment success rate under DOTS, percentage [8]
212	53%	Youth unemployment rate, aged 15-24, both sexes [8]
213	78%	Net enrolment ratio in primary education, boys [8]
214	78%	Net enrolment ratio in primary education, girls [8]
215	99%	Tuberculosis death rate per 100,000 population [8]
216	58%	Energy use (Kg oil equivalent) per $1,000 (PPP) GDP [8]
217	82%	Consumption of ozone-depleting CFCs in ODP metric tons [8]
218	61%	Debt service as % of exports of goods and services and net income from abroad [8]
219	52%	Literacy rates of 15-24 years old, both sexes, percentage [8]
220	88%	Seats held by men in national parliament [8]
221	88%	Seats held by women in national parliament [8]
222	86%	Proportion of the population using improved drinking water sources, total [8]
223	80%	Proportion of the population using improved sanitation facilities, total [8]
224	49%	Slum population as percentage of urban, percentage [8]
225	71%	Share of women in wage employment in the non-agricultural sector [8]
226	73%	People living with HIV, 15-49 years old, percentage [8]
227	39%	Women 15-24 years old, who know that a healthy-looking person can transmit HIV, percentage [8]
228	81%	Primary completion rate, both sexes [8]
229	80%	Primary completion rate, boys [8]
230	80%	Primary completion rate, girls [8]
231	95%	Carbon dioxide emissions (CO2), metric tons of CO2 per capita (CDIAC) [8]
232	82%	Consumption of all Ozone-Depleting Substances in ODP metric tons [8]
233	50%	Number of Recorded Crimes [9]
234	40%	Number of Recorded Murders Attempted [9]
235	49%	Number of Recorded Drug Crimes [9]
236	95%	Number of Disaster Related Deaths (Zero when empty) [2]
237	100%	Number of Terrorist Attacks Attempted and/or Completed (Zero when empty) [7]
238	100%	Number of Fatalities Due to Terrorist Attacks (Zero when empty) [7]
239	100%	Agricultural production index, 1999-2001=100 [10]
240	91%	Agricultural production per capita index, 1999-2001=100 [10]

Code	Data Availability	Series
241	77%	AIDS/HIV adult infections prevalence, % (UNAIDS estimates) [10]
242	80%	Balance of Payments: exports of goods, free on board, US$ (IMF) [10]
243	80%	Balance of Payments: imports of goods, free on board, US$ (IMF) [10]
244	80%	Balance of Payments: trade balance, goods and services, US$ (IMF) [10]
245	88%	Death rate, crude per 1,000 [10]
246	83%	Exchange rate, US$ per national currency (IMF) [10]
247	98%	GDP annual growth rate, 1990 prices, US$ [10]
248	74%	Imports of goods and services, current prices [10]
249	88%	Infant mortality rate per 1,000 live births [10]
250	88%	Migration, international net rate per year [10]
251	94%	Telephone lines and cellular subscribers per 100 population [10]
252	100%	Data Availability
253	95%	School age population. Primary. Total %
254	95%	School age population. Primary. Male %
255	95%	School age population. Secondary. Total %
256	95%	School age population. Secondary. Male %
257	95%	School age population. Tertiary. Total %
258	95%	School age population. Tertiary. Male %
259	93%	Enrolment in total secondary. Public and private. All programs. Total %
260	93%	Enrolment in primary. All grades. Total %
261	68%	AIDS deaths Per 1000 Pop
262	50%	Number of Recorded Crimes Per 1000 Pop
263	40%	Number of Recorded Murders Attempted Per 1000 Pop
264	48%	Number of Recorded Drug Crimes Per 1000 Pop
265	76%	Autocracy-Democracy Scale (-10 to 10) [6]
266	77%	Government Stability - Years since last government change [6]

Appendix B: Reduced List of 60 Variables

Appendix B provides a list of the variables retained after completing the correlation analysis.

Retained	Transformation	Series
100	ln	Population
110	none	Public expenditure on education as % of GDP
113	none	Largest Religion %
114	none	Largest Ethnic Group %
116	none	% time in conflict 90-2003
118	ln	Refugees
119	ln	GDP Per Capita
120	none	Political Terror
122	none	Political Rights
124	none	Agricultural land (% of land area)
126	ln	Aid per capita (current US$)
130	ln	Consumer price index (2000 = 100)
133	ln	Energy imports, net (% of energy use)
135	none	Exports of goods and services (% of GDP)
136	ln	Exports of goods and services (annual % growth)
141	none	Food imports (% of merchandise imports)
144	ln	GDP per capita growth (annual %)
152	ln	Inflation, GDP deflator (annual %)
153	ln	International tourism, expenditures (% of total imports)
155	ln	Land area (sq. km)
159	ln	Military expenditure (% of GDP)
160	ln	Military personnel (% of total labor force)
166	ln	Population density (people per sq. km)
167	ln	Population growth (annual %)
172	ln	Proportion of seats held by women in national parliament (%)
174	ln	Pupil-teacher ratio, primary
175	none	Ratio of female to male enrollments in tertiary education
177	none	Ratio of girls to boys in primary and secondary education (%)
180	ln	Rural population growth (annual %)
181	ln	Telecommunications revenue (% GDP)
182	ln	Total debt service (% of exports of goods, services and income)
184	ln	Unemployment, total (% of total labor force)
185	none	Urban population (% of total)
186	none	Use of IMF credit (DOD, current US$)
190	none	Children under five mortality rate per 1,000 live births
192	none	Children 1 year old immunized against measles, percentage
193	ln	Population undernourished, percentage

Retained	Transformation	Series
209	ln	Protected area to total surface area, percentage
211	none	Tuberculosis treatment success rate under DOTS, percentage
215	ln	Tuberculosis death rate per 100,000 population
216	ln	Energy use (Kg oil equivalent) per $1,000 (PPP) GDP
221	ln	Seats held by women in national parliament
225	none	Share of women in wage employment in the non-agricultural sector
231	ln	Carbon dioxide emissions (CO2), metric tons of CO2 per capita (CDIAC)
236	none	Number of Disaster Related Deaths (Zero when empty)
239	none	Agricultural production index, 1999-2001=100
243	ln(-)	Balance of Payments: imports of goods, free on board, US$ (IMF)
244	none	Balance of Payments: trade balance, goods and services, US$ (IMF)
246	ln	Exchange rate, US$ per national currency (IMF)
247	none	GDP annual growth rate, 1990 prices, US$
248	ln	Imports of goods and services, current prices
250	none	Migration, international net rate per year
252	none	Count of entries
253	none	School age population. Primary. Total %
257	none	School age population. Tertiary. Total %
259	none	Enrolment in total secondary. Public and private. All programmes. Total %
262	ln	Number of Recorded Crimes Per 1000 Pop
263	ln	Number of Recorded Murders Attempted Per 1000 Pop
264	ln	Number of Recorded Drug Crimes Per 1000 Pop
266	ln	Government Stability - Years since last government change

Appendix C: Nations Analyzed

Afghanistan
Albania
Algeria
Andorra
Angola
Anguilla
Antigua and Barbuda
Argentina
Armenia
Aruba
Australia
Austria
Azerbaijan
Bahamas
Bahrain
Bangladesh
Barbados
Belarus
Belgium
Belize
Benin
Bermuda
Bhutan
Bolivia
Bosnia and Herzegovina
Botswana
Brazil
Brunei
Bulgaria
Burkina Faso
Burma
Burundi
Cambodia
Cameroon
Canada
Cape Verde
Cayman Islands
Central African Republic
Chad
Chile
China
Colombia
Comoros
Congo
Congo, DRC
Costa Rica
Cote d'Ivoire
Croatia
Cuba
Cyprus
Czech Republic
Denmark
Djibouti
Dominica
Dominican Republic
East Timor
Ecuador
Egypt
El Salvador
Equatorial Guinea
Eritrea
Estonia
Ethiopia
Fiji
Finland
France
French Polynesia
Gabon
Gambia, The
Gaza Strip
Georgia
Germany
Ghana
Greece
Grenada
Guam
Guatemala
Guinea
Guinea-Bissau
Guyana
Haiti
Honduras
Hong Kong
Hungary
Iceland
India
Indonesia
Iran
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Kiribati
Korea, North
Korea, South
Kuwait
Kyrgyzstan
Laos
Latvia
Lebanon
Lesotho
Liberia
Libya
Liechtenstein
Lithuania
Luxembourg
Macau
Macedonia
Madagascar
Malawi
Malaysia
Maldives
Mali
Malta
Marshall Islands
Mauritania
Mauritius
Mexico
Micronesia
Moldova
Mongolia
Morocco
Mozambique
Namibia
Nepal
Netherlands
Netherlands Antilles
New Caledonia
New Zealand
Nicaragua
Niger
Nigeria
Norway
Oman
Pakistan
Palau

Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland
Portugal
Puerto Rico
Qatar
Romania
Russia
Rwanda
St Kitts and Nevis
St Lucia
St Vincent and the Grenadines
Samoa
San Marino
Sao Tome and Principe
Saudi Arabia
Senegal
Serbia
Seychelles
Sierra Leone
Singapore
Slovakia
Slovenia
Solomon Islands
Somalia
South Africa
Spain
Sri Lanka
Sudan
Suriname
Swaziland
Sweden
Switzerland
Syria
Tajikistan
Tanzania
Thailand
Togo
Tonga
Trinidad and Tobago
Tunisia
Turkey
Turkmenistan
Uganda
Ukraine
United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Vanuatu
Venezuela
Vietnam
Yemen
Zambia
Zimbabwe

Appendix D: States in Crisis – Model Output

This table provides a ranked listing of states in order of their second discriminant function scores, also known as the Big Picture. Shown are the prior and posterior classifications, the calculated probability of belonging to each group, and both discriminant function scores. Countries listed first are most likely to experience crises, based on the finding in this thesis.

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	**F2**
Burundi	Gap	Gap	0.001	0.999	0.000	-2.322	**-3.356**
Congo, DRC	Gap	Gap	0.001	0.997	0.002	-0.681	**-3.147**
Sierra Leone	Gap	Gap	0.001	0.999	0.000	-3.913	**-3.120**
Haiti	Gap	Gap	0.001	0.997	0.002	-0.743	**-3.017**
Equatorial Guinea	Gap	Gap	0.001	0.999	0.000	-3.121	**-2.980**
Rwanda	Gap	Gap	0.001	0.999	0.000	-2.783	**-2.952**
Eritrea	Gap	Gap	0.001	0.998	0.001	-1.169	**-2.904**
Somalia	Gap	Gap	0.002	0.998	0.000	-2.059	**-2.882**
Zimbabwe	Gap	Gap	0.001	0.776	0.223	1.046	**-2.860**
Guinea-Bissau	Gap	Gap	0.002	0.998	0.000	-3.339	**-2.857**
Chad	Gap	Gap	0.002	0.990	0.008	-0.324	**-2.767**
Togo	Gap	Gap	0.002	0.996	0.003	-0.741	**-2.753**
Angola	Gap	Gap	0.002	0.998	0.000	-1.790	**-2.748**
Comoros	Gap	Gap	0.003	0.997	0.000	-2.676	**-2.661**
Central African Republic	Gap	Gap	0.003	0.996	0.000	-1.447	**-2.565**
Afghanistan	Gap	Gap	0.002	0.762	0.236	0.940	**-2.560**
Malawi	Gap	Gap	0.003	0.987	0.010	-0.348	**-2.535**
Korea, North	Gap	Gap	0.003	0.992	0.005	-0.604	**-2.529**
Cameroon	Gap	Gap	0.003	0.992	0.005	-0.575	**-2.526**
Tajikistan	Gap	Gap	0.004	0.996	0.000	-2.166	**-2.472**
Niger	Gap	Gap	0.004	0.996	0.000	-1.585	**-2.468**
Ethiopia	Gap	Gap	0.004	0.994	0.002	-1.049	**-2.418**
Yemen	Gap	Gap	0.003	0.758	0.239	0.884	**-2.418**
Liberia	Gap	Gap	0.005	0.995	0.000	-2.816	**-2.396**
Guinea	Gap	Gap	0.005	0.995	0.000	-1.755	**-2.393**
Uzbekistan	Gap	Gap	0.005	0.979	0.017	-0.237	**-2.330**
Nepal	Gap	Gap	0.003	0.705	0.292	0.944	**-2.330**
Sudan	Gap	**Rim**	0.001	0.330	0.669	1.525	**-2.314**
Congo	Gap	Gap	0.006	0.991	0.003	-0.854	**-2.271**
Iraq	Gap	Gap	0.006	0.985	0.010	-0.461	**-2.264**
Laos	Gap	Gap	0.007	0.992	0.002	-1.126	**-2.212**
Gambia, The	Gap	Gap	0.009	0.991	0.000	-3.262	**-2.197**

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	**F2**
Cote d'Ivoire	Gap	Gap	0.007	0.989	0.003	-0.902	**-2.163**
Djibouti	Gap	Gap	0.008	0.991	0.000	-1.826	**-2.149**
Burkina Faso	Gap	Gap	0.008	0.991	0.001	-1.225	**-2.147**
Zambia	Gap	Gap	0.008	0.991	0.000	-1.649	**-2.142**
Uganda	Gap	Gap	0.009	0.987	0.004	-0.849	**-2.093**
Cambodia	Gap	Gap	0.011	0.987	0.002	-1.280	**-1.989**
Swaziland	Gap	Gap	0.011	0.981	0.008	-0.691	**-1.968**
Pakistan	Rim	Rim	0.001	0.080	0.919	1.968	**-1.864**
Anguilla	Gap	Gap	0.019	0.981	0.000	-2.330	**-1.811**
Mauritania	Gap	Gap	0.017	0.979	0.004	-1.049	**-1.790**
Tanzania	Gap	Gap	0.018	0.977	0.005	-0.943	**-1.774**
Turkmenistan	Gap	Gap	0.019	0.980	0.001	-1.550	**-1.772**
Burma	Gap	Gap	0.018	0.955	0.027	-0.316	**-1.726**
Mozambique	Gap	Gap	0.023	0.973	0.004	-1.039	**-1.663**
Mali	Gap	Gap	0.024	0.975	0.001	-1.467	**-1.662**
Bangladesh	Gap	**Rim**	0.005	0.285	0.710	1.310	**-1.660**
Sao Tome and Principe	Gap	Gap	0.027	0.972	0.001	-1.661	**-1.618**
Kenya	Gap	Gap	0.013	0.590	0.397	0.807	**-1.617**
Maldives	Gap	Gap	0.029	0.970	0.000	-2.516	**-1.616**
Nigeria	Gap	**Rim**	0.007	0.339	0.653	1.189	**-1.602**
Paraguay	Gap	**Rim**	0.001	0.042	0.957	2.093	**-1.580**
Tonga	Core	**Gap**	0.031	0.968	0.001	-1.836	**-1.562**
Saint Kitts and Nevis	Gap	Gap	0.032	0.967	0.001	-1.517	**-1.539**
Solomon Islands	Gap	Gap	0.038	0.961	0.000	-1.995	**-1.477**
Madagascar	Gap	Gap	0.040	0.959	0.001	-1.635	**-1.438**
Guatemala	Gap	Gap	0.036	0.826	0.138	0.170	**-1.343**
Bhutan	Gap	Gap	0.054	0.945	0.001	-1.912	**-1.314**
Trinidad and Tobago	Gap	Gap	0.039	0.831	0.130	0.128	**-1.310**
Armenia	Gap	Gap	0.053	0.946	0.001	-1.665	**-1.309**
Benin	Gap	Gap	0.055	0.945	0.001	-1.952	**-1.309**
Azerbaijan	Gap	Gap	0.055	0.943	0.002	-1.490	**-1.287**
Gabon	Gap	Gap	0.059	0.875	0.066	-0.201	**-1.168**
Thailand	Rim	Rim	0.000	0.005	0.995	2.701	**-1.159**
Botswana	Gap	Gap	0.054	0.746	0.200	0.246	**-1.122**
Papua New Guinea	Gap	Gap	0.066	0.858	0.076	-0.169	**-1.108**
Antigua and Barbuda	Gap	Gap	0.099	0.899	0.002	-1.515	**-1.010**
India	Rim	Rim	0.000	0.001	0.999	3.151	**-1.004**
Saint Vincent and the Grenadines	Gap	Gap	0.100	0.896	0.004	-1.338	**-0.995**
Bolivia	Gap	Gap	0.083	0.809	0.108	-0.077	**-0.978**
Syria	Gap	**Rim**	0.007	0.080	0.912	1.558	**-0.959**
Sri Lanka	Gap	Gap	0.088	0.789	0.124	-0.032	**-0.943**
Iran	Gap	**Rim**	0.000	0.003	0.997	2.800	**-0.925**
Vietnam	Gap	Gap	0.099	0.787	0.114	-0.084	**-0.893**
Nicaragua	Gap	Gap	0.113	0.852	0.035	-0.553	**-0.889**
Senegal	Gap	Gap	0.134	0.865	0.001	-1.850	**-0.876**

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	**F2**
Dominican Republic	Gap	Gap	0.061	0.488	0.451	0.588	**-0.864**
Venezuela	Gap	**Rim**	0.035	0.270	0.695	0.957	**-0.840**
Aruba	Gap	Gap	0.172	0.828	0.000	-2.741	**-0.784**
Algeria	Rim	Rim	0.005	0.039	0.956	1.763	**-0.777**
Honduras	Gap	Gap	0.150	0.823	0.027	-0.692	**-0.754**
Gaza Strip	Gap	Gap	0.150	0.810	0.039	-0.557	**-0.741**
Kyrgyzstan	Gap	Gap	0.159	0.812	0.029	-0.683	**-0.722**
Mongolia	Core	**Gap**	0.162	0.805	0.033	-0.633	**-0.708**
Dominica	Gap	Gap	0.219	0.781	0.000	-3.056	**-0.667**
Vanuatu	Core	**Gap**	0.224	0.776	0.000	-2.819	**-0.644**
Philippines	Rim	Rim	0.004	0.023	0.972	1.892	**-0.624**
Seychelles	Gap	Gap	0.220	0.779	0.001	-1.897	**-0.615**
Saudi Arabia	Rim	Rim	0.002	0.010	0.988	2.191	**-0.609**
Georgia	Gap	Gap	0.214	0.781	0.005	-1.368	**-0.605**
Lesotho	Gap	Gap	0.148	0.599	0.253	0.173	**-0.585**
Kazakhstan	Gap	Gap	0.187	0.709	0.104	-0.224	**-0.573**
China	Rim	Rim	0.007	0.028	0.966	1.786	**-0.532**
Bermuda	Gap	Gap	0.272	0.727	0.000	-2.301	**-0.509**
Guyana	Gap	Gap	0.244	0.734	0.022	-0.844	**-0.499**
Kuwait	Gap	Gap	0.135	0.443	0.422	0.429	**-0.482**
Jamaica	Gap	Gap	0.278	0.719	0.003	-1.564	**-0.463**
Namibia	Gap	Gap	0.225	0.660	0.115	-0.209	**-0.461**
Colombia	Gap	**Rim**	0.117	0.359	0.524	0.571	**-0.446**
Libya	Gap	Gap	0.162	0.471	0.366	0.332	**-0.433**
Belize	Gap	Gap	0.238	0.621	0.140	-0.137	**-0.406**
Morocco	Rim	Rim	0.032	0.094	0.874	1.237	**-0.399**
Moldova	Core	**Gap**	0.307	0.686	0.007	-1.289	**-0.388**
El Salvador	Gap	Gap	0.215	0.547	0.238	0.096	**-0.386**
Egypt	Gap	**Rim**	0.020	0.056	0.924	1.438	**-0.382**
Suriname	Gap	Gap	0.228	0.561	0.211	0.038	**-0.373**
Oman	Gap	Gap	0.275	0.649	0.076	-0.394	**-0.373**
Netherlands Antilles	Gap	Gap	0.356	0.644	0.000	-2.945	**-0.366**
Ghana	Gap	Gap	0.269	0.623	0.108	-0.255	**-0.360**
Fiji	Core	**Gap**	0.311	0.671	0.018	-0.943	**-0.358**
Cuba	Gap	Gap	0.314	0.671	0.015	-1.010	**-0.356**
Grenada	Gap	Gap	0.358	0.642	0.000	-2.801	**-0.355**
Jordan	Gap	Gap	0.331	0.662	0.007	-1.306	**-0.339**
East Timor	Gap	Gap	0.305	0.640	0.055	-0.528	**-0.328**
Bahrain	Gap	Gap	0.357	0.634	0.009	-1.220	**-0.285**
Albania	Gap	Gap	0.356	0.603	0.041	-0.655	**-0.239**
Panama	Gap	Gap	0.395	0.581	0.024	-0.860	**-0.187**
Saint Lucia	Gap	Gap	0.454	0.545	0.000	-2.318	**-0.160**
Lebanon	Gap	Gap	0.434	0.557	0.009	-1.246	**-0.143**
Indonesia	Rim	Rim	0.000	0.000	1.000	3.726	**-0.138**
Cape Verde	Gap	Gap	0.368	0.487	0.145	-0.166	**-0.111**
Malta	Core	**Gap**	0.478	0.521	0.001	-2.105	**-0.109**

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	**F2**
Macedonia	Gap	**Core**	0.514	0.485	0.001	-2.152	**-0.047**
Belarus	Core	**Gap**	0.450	0.495	0.055	-0.563	**-0.047**
Samoa	Core	Core	0.555	0.445	0.000	-2.714	**0.000**
New Caledonia	Core	Core	0.528	0.469	0.003	-1.639	**0.001**
Ecuador	Gap	**Rim**	0.085	0.093	0.822	1.029	**0.019**
Brazil	Rim	Rim	0.006	0.007	0.987	2.058	**0.075**
Tunisia	Gap	**Core**	0.387	0.342	0.271	0.112	**0.078**
United Arab Emirates	Gap	**Rim**	0.037	0.036	0.928	1.399	**0.089**
Peru	Gap	**Rim**	0.055	0.052	0.893	1.242	**0.090**
Mauritius	Gap	**Core**	0.532	0.407	0.062	-0.515	**0.114**
Bosnia and Herzegovina	Gap	**Core**	0.608	0.391	0.001	-2.173	**0.120**
Micronesia	Core	Core	0.605	0.378	0.016	-1.009	**0.181**
Bahamas	Core	Core	0.616	0.371	0.014	-1.078	**0.195**
Qatar	Gap	**Rim**	0.300	0.195	0.505	0.483	**0.227**
Puerto Rico	Gap	**Core**	0.667	0.331	0.002	-1.812	**0.248**
Brunei	Gap	**Rim**	0.355	0.206	0.439	0.391	**0.273**
South Africa	Rim	Rim	0.017	0.010	0.973	1.783	**0.310**
Kiribati	Core	Core	0.677	0.311	0.012	-1.103	**0.312**
Turkey	Rim	Rim	0.002	0.001	0.997	2.637	**0.338**
Serbia	Gap	**Core**	0.738	0.260	0.001	-1.900	**0.393**
French Polynesia	Core	Core	0.746	0.254	0.001	-2.198	**0.396**
Israel	Gap	**Core**	0.726	0.266	0.009	-1.216	**0.407**
Palau	Gap	**Core**	0.744	0.251	0.005	-1.448	**0.432**
Russia	Rim	Rim	0.038	0.017	0.945	1.528	**0.454**
Singapore	Gap	**Core**	0.762	0.221	0.017	-0.953	**0.520**
Bulgaria	Gap	**Core**	0.782	0.210	0.008	-1.218	**0.543**
Costa Rica	Gap	**Core**	0.559	0.171	0.270	0.159	**0.543**
Barbados	Gap	**Core**	0.811	0.189	0.000	-2.607	**0.544**
Croatia	Gap	**Core**	0.758	0.212	0.030	-0.733	**0.545**
Mexico	Rim	Rim	0.009	0.003	0.988	2.125	**0.628**
Guam	Core	Core	0.744	0.167	0.089	-0.293	**0.660**
Iceland	Core	Core	0.863	0.133	0.004	-1.414	**0.774**
Uruguay	Core	Core	0.825	0.134	0.040	-0.563	**0.788**
Hong Kong	Core	**Rim**	0.323	0.047	0.630	0.795	**0.895**
Argentina	Rim	Rim	0.139	0.021	0.840	1.200	**0.904**
Slovakia	Core	Core	0.881	0.105	0.014	-0.928	**0.907**
Malaysia	Rim	Rim	0.100	0.014	0.887	1.354	**0.942**
Ukraine	Core	Core	0.629	0.076	0.295	0.308	**0.955**
Cyprus	Gap	**Core**	0.918	0.082	0.000	-2.352	**0.977**
Chile	Rim	**Core**	0.540	0.057	0.402	0.499	**1.021**
Marshall Islands	Core	Core	0.922	0.077	0.001	-1.884	**1.022**
Macau	Core	Core	0.895	0.068	0.037	-0.491	**1.127**
San Marino	Core	Core	0.941	0.059	0.000	-2.115	**1.141**
Cayman Islands	Gap	**Core**	0.943	0.057	0.000	-2.434	**1.145**
Romania	Gap	**Core**	0.562	0.042	0.396	0.539	**1.177**
Latvia	Core	Core	0.926	0.060	0.014	-0.835	**1.182**

Observation	Barnett	Model	Pr(Core)	Pr(Gap)	Pr(Rim)	F1	**F2**
New Zealand	Core	Core	0.906	0.056	0.038	-0.456	**1.215**
Luxembourg	Core	Core	0.937	0.054	0.009	-0.997	**1.222**
Liechtenstein	Core	Core	0.955	0.044	0.001	-1.611	**1.295**
Slovenia	Core	Core	0.956	0.040	0.003	-1.280	**1.348**
Andorra	Gap	**Core**	0.961	0.039	0.001	-1.770	**1.349**
Norway	Core	Core	0.954	0.036	0.010	-0.883	**1.414**
Estonia	Core	Core	0.965	0.032	0.003	-1.251	**1.453**
Greece	Rim	**Core**	0.916	0.029	0.055	-0.212	**1.514**
Australia	Core	Core	0.735	0.024	0.241	0.405	**1.536**
Czech Republic	Core	Core	0.962	0.025	0.013	-0.713	**1.585**
Hungary	Core	Core	0.941	0.025	0.034	-0.361	**1.589**
Portugal	Core	Core	0.932	0.025	0.043	-0.273	**1.595**
Lithuania	Core	Core	0.972	0.022	0.006	-0.954	**1.634**
Korea, South	Rim	Rim	0.159	0.004	0.837	1.455	**1.688**
Ireland	Core	Core	0.977	0.017	0.006	-0.905	**1.752**
Poland	Core	Core	0.841	0.015	0.143	0.267	**1.784**
Denmark	Core	Core	0.985	0.014	0.000	-1.902	**1.788**
Finland	Core	Core	0.986	0.013	0.002	-1.379	**1.859**
Switzerland	Core	Core	0.988	0.011	0.001	-1.605	**1.903**
Austria	Core	Core	0.985	0.012	0.003	-1.139	**1.908**
United Kingdom	Core	Core	0.971	0.011	0.018	-0.468	**1.943**
Canada	Core	Core	0.901	0.010	0.089	0.149	**1.983**
Spain	Core	Core	0.890	0.010	0.100	0.198	**1.989**
Sweden	Core	Core	0.991	0.009	0.000	-1.757	**2.021**
Italy	Core	Core	0.982	0.009	0.008	-0.704	**2.029**
Netherlands	Core	Core	0.991	0.008	0.001	-1.417	**2.058**
France	Core	Core	0.972	0.008	0.020	-0.353	**2.128**
Belgium	Core	Core	0.993	0.006	0.001	-1.432	**2.221**
Japan	Core	Core	0.951	0.005	0.044	0.011	**2.324**
Germany	Core	Core	0.994	0.003	0.003	-0.973	**2.455**
United States	Core	Core	0.972	0.003	0.025	-0.108	**2.558**

Appendix E: Failed States Index Comparison

The Fund for Peace (FFP) publishes an annual Failed States Index which provides scores for each country indicating their current stability. This appendix provides a comparison between the 2006 Index and the scores each nation received on the Big Picture Function as defined in this study. The two lists were compared using Spearman's Rank Correlation Coefficient to test whether or not there are statistically significant differences between the ranks assigned to each country using the two methods. Note that the FFP assessed 146 of the 200 nations analyzed in this study, and this table includes only those countries.

Spearman's Rank Correlation coefficient is calculated using the differences between rankings for the two methods, *d*.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

With *n* equal to 146, we obtain a value of 0.849, meaning there is an approximately 85% correlation between the FFP and Function 2 country rankings. To see if this correlation is statistically different from zero, we calculate the t-statistic

$$t = \frac{\rho}{\sqrt{(1 - \rho^2)/(n - 2)}}$$

for which we obtain a value of 19.28, which is significant at the 99% confidence level. In other words, there appears to be a significant correlation between the FFP and Function 2 rankings, further indicating that our discriminant function may be useful for classifying failing states.

Provided in the table are the FFP and Big Picture scores and rankings, and the differences between the two.

Observation	Scores FFP	Scores Function 2	Rankings FFP	Rankings Function 2	Differences d	Differences d^2
Sudan	112.3	-2.314	1	27	-26	676
Congo, DRC	110.1	-3.147	2	2	0	0
Cote d'Ivoire	109.2	-2.163	3	31	-28	784
Iraq	109.0	-2.264	4	28	-24	576
Zimbabwe	108.9	-2.860	5	9	-4	16
Chad	105.9	-2.767	6	11	-5	25
Somalia	105.9	-2.882	7	8	-1	1
Haiti	104.6	-3.017	8	4	4	16
Pakistan	103.1	-1.864	9	36	-27	729
Afghanistan	99.8	-2.560	10	15	-5	25
Guinea	99.0	-2.393	11	24	-13	169
Liberia	99.0	-2.396	12	23	-11	121
Central African Republic	97.5	-2.565	13	14	-1	1
Korea, North	97.3	-2.529	14	17	-3	9
Burundi	96.7	-3.356	15	1	14	196
Sierra Leone	96.6	-3.120	16	3	13	169
Yemen	96.6	-2.418	17	22	-5	25
Burma	96.5	-1.726	18	40	-22	484
Bangladesh	96.3	-1.660	19	43	-24	576
Nepal	95.4	-2.330	20	26	-6	36
Uganda	94.5	-2.093	21	34	-13	169
Nigeria	94.4	-1.602	22	45	-23	529
Uzbekistan	94.4	-2.330	23	25	-2	4
Rwanda	92.9	-2.952	24	6	18	324
Sri Lanka	92.4	-0.943	25	59	-34	1156
Ethiopia	91.9	-2.418	26	21	5	25
Colombia	91.8	-0.446	27	78	-51	2601
Kyrgyzstan	90.3	-0.722	28	68	-40	1600
Malawi	89.8	-2.535	29	16	13	169
Burkina Faso	89.7	-2.147	30	32	-2	4
Egypt	89.5	-0.382	31	83	-52	2704
Indonesia	89.2	-0.138	32	91	-59	3481
Kenya	88.6	-1.617	33	44	-11	121
Syria	88.6	-0.959	34	58	-24	576
Bosnia and Herzegovina	88.5	0.120	35	99	-64	4096
Cameroon	88.4	-2.526	36	18	18	324
Angola	88.3	-2.748	37	13	24	576
Togo	88.3	-2.753	38	12	26	676
Bhutan	87.9	-1.314	39	48	-9	81
Laos	87.9	-2.212	40	29	11	121

	Scores		Rankings		Differences	
Observation	FFP	Function 2	FFP	Function 2	d	d^2
Mauritania	87.8	-1.790	41	37	4	16
Tajikistan	87.7	-2.472	42	19	23	529
Russia	87.1	0.454	43	104	-61	3721
Niger	87.0	-2.468	44	20	24	576
Turkmenistan	86.1	-1.772	45	39	6	36
Guinea-Bissau	85.4	-2.857	46	10	36	1296
Cambodia	85.0	-1.989	47	35	12	144
Dominican Republic	85.0	-0.864	48	64	-16	256
Papua New Guinea	84.6	-1.108	49	55	-6	36
Belarus	84.5	-0.047	50	93	-43	1849
Guatemala	84.3	-1.343	51	47	4	16
Equatorial Guinea	84.0	-2.980	52	5	47	2209
Iran	84.0	-0.925	53	60	-7	49
Eritrea	83.9	-2.904	54	7	47	2209
Serbia	83.8	0.393	55	102	-47	2209
Bolivia	82.9	-0.978	56	57	-1	1
China	82.5	-0.532	57	74	-17	289
Moldova	82.5	-0.388	58	81	-23	529
Nicaragua	82.4	-0.889	59	62	-3	9
Georgia	82.2	-0.605	60	72	-12	144
Azerbaijan	81.9	-1.287	61	51	10	100
Cuba	81.9	-0.356	62	86	-24	576
Ecuador	81.2	0.019	63	94	-31	961
Venezuela	81.2	-0.840	64	65	-1	1
Lebanon	80.5	-0.143	65	90	-25	625
Zambia	79.6	-2.142	66	33	33	1089
Israel	79.4	0.407	67	103	-36	1296
Peru	79.2	0.090	68	97	-29	841
Philippines	79.2	-0.624	69	70	-1	1
Vietnam	78.6	-0.893	70	61	9	81
Tanzania	78.3	-1.774	71	38	33	1089
Algeria	77.8	-0.777	72	66	6	36
Saudi Arabia	77.2	-0.609	73	71	2	4
Jordan	77.0	-0.339	74	87	-13	169
Honduras	76.7	-0.754	75	67	8	64
Morocco	76.5	-0.399	76	80	-4	16
El Salvador	76.1	-0.386	77	82	-5	25
Macedonia	75.1	-0.047	78	92	-14	196
Thailand	74.9	-1.159	79	53	26	676
Mozambique	74.8	-1.663	80	41	39	1521
Mali	74.6	-1.662	81	42	39	1521
Turkey	74.4	0.338	82	101	-19	361
Gambia, The	74.0	-2.197	83	30	53	2809
Gabon	73.6	-1.168	84	52	32	1024
Mexico	73.1	0.628	85	109	-24	576
Ukraine	72.9	0.955	86	114	-28	784
Paraguay	72.0	-1.580	87	46	41	1681

	Scores		Rankings		Differences	
Observation	FFP	Function 2	FFP	Function 2	d	d^2
Kazakhstan	71.9	-0.573	88	73	15	225
Armenia	71.5	-1.309	89	49	40	1600
Benin	70.9	-1.309	90	50	40	1600
Namibia	70.7	-0.461	91	77	14	196
Cyprus	70.5	0.977	92	115	-23	529
India	70.4	-1.004	93	56	37	1369
Albania	68.6	-0.239	94	88	6	36
Libya	68.5	-0.433	95	79	16	256
Botswana	66.9	-1.122	96	54	42	1764
Jamaica	66.8	-0.463	97	76	21	441
Malaysia	66.1	0.942	98	113	-15	225
Senegal	66.1	-0.876	99	63	36	1296
Tunisia	65.4	0.078	100	96	4	16
Brazil	63.1	0.075	101	95	6	36
Romania	62.6	1.177	102	117	-15	225
Bulgaria	62.1	0.543	103	106	-3	9
Croatia	61.9	0.545	104	108	-4	16
Kuwait	60.8	-0.482	105	75	30	900
Ghana	60.5	-0.360	106	85	21	441
Panama	59.6	-0.187	107	89	18	324
Mongolia	58.4	-0.708	108	69	39	1521
Latvia	56.2	1.182	109	118	-9	81
South Africa	55.7	0.310	110	100	10	100
Estonia	51.0	1.453	111	122	-11	121
Slovakia	49.9	0.907	112	112	0	0
Lithuania	49.7	1.634	113	128	-15	225
Costa Rica	49.6	0.543	114	107	7	49
Poland	47.9	1.784	115	131	-16	256
Hungary	46.7	1.589	116	126	-10	100
Oman	43.8	-0.373	117	84	33	1089
Mauritius	41.9	0.114	118	98	20	400
Czech Republic	41.8	1.585	119	125	-6	36
Uruguay	41.2	0.788	120	110	10	100
Greece	41.1	1.514	121	123	-2	4
Argentina	40.8	0.904	122	111	11	121
Korea, South	39.9	1.688	123	129	-6	36
Germany	39.7	2.455	124	145	-21	441
Spain	37.4	1.989	125	138	-13	169
Slovenia	36.8	1.348	126	120	6	36
Italy	35.1	2.029	127	140	-13	169
United States	34.5	2.558	128	146	-18	324
France	34.3	2.128	129	142	-13	169
United Kingdom	34.2	1.943	130	136	-6	36
Portugal	32.7	1.595	131	127	4	16
Chile	32.0	1.021	132	116	16	256
Singapore	30.8	0.520	133	105	28	784
Netherlands	28.1	2.058	134	141	-7	49

	Scores		Rankings		Differences	
Observation	FFP	Function 2	FFP	Function 2	d	d^2
Japan	28.0	2.324	135	144	-9	81
Austria	26.1	1.908	136	135	1	1
Denmark	24.8	1.788	137	132	5	25
Belgium	24.0	2.221	138	143	-5	25
Canada	23.1	1.983	139	137	2	4
Australia	22.0	1.536	140	124	16	256
New Zealand	19.4	1.215	141	119	22	484
Switzerland	18.7	1.903	142	134	8	64
Ireland	18.6	1.752	143	130	13	169
Finland	18.2	1.859	144	133	11	121
Sweden	18.2	2.021	145	139	6	36
Norway	16.8	1.414	146	121	25	625

Bibliography

9-11 Commission. *9/11 Commission Report: Final Report of the National Commission on Terrorist Attacks Upon the United States*. National Commission on Terrorist Attacks Upon the United States, 2004.

Allison, P.D. *Missing Data*. Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-136. Thousand Oaks, CA: Sage, 2001.

Baker, Pauline H., The Fund for Peace. "Agent-Based Models and Other Analytic Tools in Support of Stability Operations." Briefing to Military Operations Research Symposium, October 2005.

Banks, Jerry, John S. Carson II, Barry L. Nelson, David M. Nicol. *Discrete Event Simulation.* New Jersey: Prentice-Hall, 2005.

Barber, Benjamin. *Jihad vs. McWorld: Terrorism's Challenge to Democracy*. New York: Random House, 2001.

Barnett, Thomas P.M. "The Pentagon's New Map," *Esquire*, March 2003.

Barnett, Thomas P.M. *Blueprint for Action: A Future Worth Creating*. New York: Penguin Group, 2005.

Bredel, Ralf. *Long-Term Conflict Prevention and Industrial Development*. Boston: Martinus Nijhoff Publishers, 2003.

Bremer, Ian. *The J Curve: A New Way to Understand Why Nations Rise and Fall*. Simon & Schuster, 2006.

Brown, Michael E. "The Causes of Internal Conflict: An Overview" in *Nationalism and Ethnic Conflict*. Ed. Michael E. Brown, Owen R. Cote Jr., Sean M. Lynn-Jones and Steven E. Miller. Cambridge MA: The MIT Press, 2001.

Carment, David and Albrecht Schnabel. *Conflict Prevention: Path to Peace or Grand Illusion?*. New York: United Nations University Press, 2003.

Chantala, Kim and Suchindran. Multiple Imputation for Missing Data Briefing. http://www.cpc.unc.edu/services/computer/presentations/mi_presentation2.pdf. Last accessed 20 December 2006.

Congressional Budget Office (CBO), "Estimated Appropriations Provided for Iraq and the War on Terrorism, 2001-2006", Aug 2006. http://www.cbo.gov/ftpdocs/75xx/doc7506/GWOT_Tables_2006_08.pdf

Department of Defense Directive Number 3000.05, Military Support for Stability, Security, Transition, and Reconstruction (SSTR) Operations. 28 November 2005.

Dillon, William R. and Matthew Goldstein. *Multivariate Analysis: Methods and Applications*. Wiley, 1984.

Durch, William J. "Are There Peace/Stability Operations in Your Future?". Briefing for the Chairman of the Joint Chiefs of Staff Seminar, 12 June 2002.

Dziedzic, Michael J. "Conclusion" in *The Quest for Viable Peace: International Intervention and Strategies for Conflict Transformation*. Ed. Jack Covey, Michael Dziedzic and Leonard R. Hawley. Washington DC: United States Institute of Peace Press, 2005.

Dziedzic, Michael J. and Len Hawley. "Introduction" in *The Quest for Viable Peace: International Intervention and Strategies for Conflict Transformation*. Ed. Jack Covey, Michael Dziedzic and Leonard R. Hawley. Washington DC: United States Institute of Peace Press, 2005.

Esty, Daniel C. *et al*. State Failure Task Force Report. Political Instability/State Failure Task Force Website http://globalpolicy.gmu.edu/pitf/pitfdata.htm, accessed 29 November, 2006.

Fensterer, Gerald D. *Planning and Assessing Stability Operations: A Value Focused Approach*. MS Thesis, AFIT/ENS/07M-06. School of Operations Research, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, March 2007.

Forest, James J. F. *The Making of a Terrorist: Volume Three, Root Causes*. Praeger Security International, Connecticut, 2006.

Interactive Textbook on Clinical Symptom Research (ITCSR), Chapter 8: Statistical Models for Prognostication. http://symptomresearch.nih.gov/chapter_8/sec8/cess8pg2.htm (active 22 Feb, 2005)

Keeney, Ralph L. and Howard Raiffa. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs.* Wiley, 1976.

Lattin, James M., J. Douglas Carroll, Paul E. Green. *Analyzing Multivariate Data*. Duxbury, 2003.

Montgomery, Douglas C., Elizabeth A. Pec and G. Geoffrey Vining. *Introduction to Linear Regression Analysis.* New York: John Wiley & Sons, 2001.

Nafziger, E. Wayne and Juha Auvinen. *War, Hunger, and Displacement: An Econometric Investigation into the Sources of Humanitarian Emergencies*. Helsinki: UNU World Institute for Development Economics Research, 1997.

O'Brien, Sean P. Analyzing Complex Threats for Operations and Readiness (ACTOR): A Methodology for Forecasting Country Instability. Presented to the Military Operations Research Society Symposium, July 2002.

Statistical Analysis with Missing Data, Second Edition, by Little and Rubin.

Office of the President of the United States (OPOTUS), "National Strategy for Combating Terrorism", Feb 2003. http://www.whitehouse.gov/news/releases/2003/02/counter_terrorism/counter_terrorism_strategy.pdf

Poe, Steven C., Nicolas Rost and Sabine C. Carey. Assessing Risk and Opportunity in Conflict Studies. *Journal of Conflict Resolution*, 484-507, 2006.

Pohar, Maja, Mateha Blas, and Sandra Turk. "Comparison of Logistic Regression and Linear Discriminant Analysis: A Simulation Study," *Metodoloski zveszki*, Vol. 1, No. 1, pp 143-161, 2004.

Rotberg, Robert I. *When States Fail: Causes and Consequences*. Princeton University Press, 2004.

Rotberg, Robert I. State Failure and State Weakness in a Time of Terror. Washington DC: Brookings Institution Press, 2003.

S. 2125 Democratic Republic of the Congo Relief, Security, and Democracy Promotion Act of September 13, 2006.

Snyder, Jack and Karen Ballentine. "Nationalism and the Marketplace of Ideas" in *Nationalism and Ethnic Conflict*. Ed. Michael E. Brown, Owen R. Cote Jr., Sean M. Lynn-Jones and Steven E. Miller. Cambridge MA: The MIT Press, 2001.

StatSoft, Inc. *Electronic Statistics Textbook*. Tulsa, OK: StatSoft. WEB: http://www.statsoft.com/textbook/stathome.html, 2006.

Stewart, Frances. Root Causes of Conflict in Developing Countries. *British Medical Journal*, 342-345, February 2002.

Stewart, Frances. Crisis Prevention: Tackling Horizontal Inequalities. Paper prepared for World Bank Conference on Evaluation and Poverty Reduction, June 1999. http://www.qeh.ox.ac.uk/pdf/qehwp/qehwps33.pdf

Takeyh, Ray and Nikolas Gvosdev. Do Terrorist Networks Need a Home? The Washington Quarterly, 97-108, Summer 2002.

Tukey, John W. *Exploratory Data Analysis*. Addison-Wesley, 1977.

United Nations Resolution A/Res/55/2: *United Nations Millennium Declaration*. 18 September 2000.

Van Evera, Stephen. "Hypotheses on Nationalism and War" in *Nationalism and Ethnic Conflict*. Ed. Michael E. Brown, Owen R. Cote Jr., Sean M. Lynn-Jones and Steven E. Miller. Cambridge MA: The MIT Press, 2001.

von Winterfeldt, R. L. and Ward Edwards. *Decision Analysis and Behavioral Research*, Cambridge: Cambridge University Press, 1986.

Wackerly, Dennis D., William Mendenhall III and Richard L. Scheaffer. *Mathematical Statistics with Applications 6th Edition*. Duxbury, 2002.

Wonnacott, Ronald J. and Thomas H. Wonnacott. *Econometrics 2nd Edition*. New York, Wiley & Sons, 1979.

Winston, Wayne L. *Operations Research: Applications and Algorithms 2nd Edition*. Boston: PWS-Kent, 1991.

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14. ABSTRACT
The US is heavily involved in the first major war of the 21st Century – The Global War on Terror (GWOT). As with any militant group, the foundation of the enemy's force is their people. There are two primary strategies for defeating the terrorists and achieving victory in the GWOT. First, we must root out terrorists where they live, train, plan, and recruit and attack them militarily. Second, we must suffocate them by cutting off the supply of new soldiers willing to choose aggression or even death over their current life. This thesis helps to achieve these objectives by applying Multivariate Analysis techniques to identify the states most likely to provide asylum for terrorists. Weak and Failed States are attractive to terrorist groups looking for safe haven and recruits. Governments in these states are often unable to prevent illegal activity, and are vulnerable to corruption or takeover. Citizens of failing states often experience poverty, disease, and unemployment, and may see little hope for improvement. Terrorists can meet these disenfranchised people's basic needs and promise brighter futures for families of those willing to fight and perhaps die for the cause. Current published efforts to identify failing states primarily use Ordinary Least Squares Regression, which requires the analyst to predefine the degree to which a state is likely to fail. This thesis uses a Factor Analysis approach to identify the key indicators of state failure, and Discriminant Analysis to classify states as Stable, Borderline, or Failing based on these indicators. Furthermore, each nation's discriminant function scores are used to determine their degree of instability. The methodology is applied to 200 countries for which open source data was available on 167 variables. Results of the classification are compared with subject matter experts in the field of state failure.

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